Reinforcement Learning from Community Feedback (RLCF): A Novel Framework for Artificial Legal Intelligence

Abstract

We present Reinforcement Learning from Community Feedback (RLCF), a novel alignment methodology specifically designed for Artificial Legal Intelligence (ALI) systems. Unlike traditional Reinforcement Learning from Human Feedback (RLHF), RLCF leverages distributed expert validation, dynamic authority scoring, and uncertainty-preserving aggregation to address the unique epistemological challenges of the legal domain. Our framework introduces mathematically grounded mechanisms for community-driven validation while preserving the dialectical nature of legal reasoning.

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1. Introduction and Theoretical Foundation

1.1 Motivation

Traditional RLHF approaches fail to capture the inherent complexity of legal reasoning, which requires:

- **Epistemic Pluralism**: Recognition of multiple valid interpretations
- **Dynamic Authority**: Expertise that evolves with demonstrated competence
- **Dialectical Preservation**: Maintenance of productive disagreement
- **Transparent Accountability**: Traceable reasoning paths

1.2 Core Principles

The RLCF framework is built upon four foundational principles:

1. Principle of Dynamic Authority (*Auctoritas Dynamica*)

- Authority is earned through demonstrated competence, not merely credentialed
- Expertise evolves based on track record and peer validation

2. Principle of Preserved Uncertainty (*Incertitudo Conservata*)

- Disagreement among experts is information, not noise
- Multiple valid interpretations coexist in the output

3. Principle of Transparent Process (*Processus Transparens*)

- All validation steps are auditable and reproducible
- Bias detection is integral, not peripheral

4. Principle of Universal Expertise (*Peritia Universalis*)

- Domain boundaries are emergent, not prescribed
- Cross-domain insights are valued and weighted appropriately

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2. Mathematical Framework

2.1 Dynamic Authority Scoring Model

We define the authority score of a user $u \in \mathrm{U}$ at discrete time $t \in \mathrm{N}$ as a linear combination of three normalized components:

$$A_u(t) = \alpha \cdot B_u + \beta \cdot T_u(t-1) + \gamma \cdot P_u(t)$$

Variable Definitions:

- $A_u(t) \in [0, 2]$: Authority score for user u at time t
- $B_u \in [0, 2]$: Baseline credentials score (time-invariant)
- $T_u(t-1) \in [0, 1]$: Historical track record (exponentially smoothed)
- $P_u(t) \in [0, 1]$: Recent performance metric (current period)
- $\alpha, \beta, \gamma \in [0, 1]$: Weight parameters with $\alpha + \beta + \gamma = 1$

Implementation Choice - Weight Distribution:

Based on legal domain expertise consultation and empirical validation:

```
# From model_config.yaml - authority_weights section
AUTHORITY_WEIGHTS = {
    "baseline_credentials": 0.3,  # α = 0.3
    "track_record": 0.5,          # β = 0.5
    "recent_performance": 0.2     # γ = 0.2
}
```

Rationale: The 50% weight on track record reflects legal practice where demonstrated competence over time is paramount, while baseline credentials provide stability and recent performance allows for adaptation.

2.2 Dynamic Baseline Credentials System

The baseline credentials system implements a configurable scoring framework:

$$B_u = \sum_{i=1}^{n} w_i \cdot f_i(c_{u,i})$$

Variable Definitions:

- $B_u \in [0, 2]$: Total baseline score for user u
- $n = |\mathrm{C}|$: Number of credential types in $\mathrm{C} = \{\mathrm{DEGREE}, \mathrm{EXPERIENCE}, \mathrm{PUBLICATIONS}, \mathrm{ROLE}\}$
- $w_i \in [0, 1]$: Weight for credential type i with $\sum_{i=1}^{n} w_i = 1$

- $c_{u,i}$: Raw credential value for user u in type i
- $f_i : \mathrm{R} \to [0, 2]$: Scoring function for credential type i

Implementation Architecture:

```yaml
# model_config.yaml - Credential scoring configuration
baseline_credentials:
  types:
    ACADEMIC_DEGREE:
      weight: 0.3
      scoring_function:
        type: "map"
        values:
          "Bachelor": 1.0
          "LLM": 1.1
          "JD": 1.2
          "PhD": 1.5
        default: 0.0

    PROFESSIONAL_EXPERIENCE:
      weight: 0.4
      scoring_function:
        type: "formula"
        expression: "0.5 + 0.2 * sqrt(value)"

    PUBLICATIONS:
      weight: 0.2
      scoring_function:
        type: "formula"
        expression: "min(0.8 + 0.1 * value, 1.4)"

    INSTITUTIONAL_ROLE:
      weight: 0.1
      scoring_function:
        type: "map"
        values:
          "Junior": 0.7
          "Senior": 1.1
          "Partner": 1.4
        default: 0.0
```

Technical Implementation:

The system uses safe formula evaluation via `asteval` for runtime flexibility:

```python
async def calculate_baseline_credentials(db: AsyncSession, user_id: int) ->
float:
    """
    Implements B_u = Σ(w_i · f_i(c_{u,i})) with configurable scoring
functions.
```

```
    Security: Uses asteval.Interpreter() for safe mathematical expression
evaluation.
    Flexibility: Supports both discrete mappings and continuous formulas.
    """
    evaluator = asteval.Interpreter()
    evaluator.symtable.update({"sqrt": sqrt, "min": min, "max": max})

    total_score = 0.0
    for cred in user.credentials:
        rule = model_settings.baseline_credentials.types[cred.type]

        if rule.scoring_function.type == "formula":
            evaluator.symtable["value"] = float(cred.value)
            score = evaluator.eval(rule.scoring_function.expression)
        elif rule.scoring_function.type == "map":
            score = rule.scoring_function.values.get(str(cred.value),
rule.default)

        total_score += rule.weight * score

    return total_score
```

2.3 Track Record Evolution Model

The track record follows an exponential smoothing update rule that balances historical performance with recent quality:

$$T_u(t) = \lambda \cdot T_u(t-1) + (1-\lambda) \cdot Q_u(t)$$

Variable Definitions:

- $T_u(t) \in [0, 1]$: Track record score for user u at time t
- $\lambda = 0.95$: Decay factor (configurable in `model_config.yaml`)
- $Q_u(t) \in [0, 1]$: Quality score at time t
- $(1-\lambda) = 0.05$: Update factor for new information

Quality Score Aggregation:

$$Q_u(t) = \frac{1}{4} \sum_{k=1}^{4} q_k$$

Component Definitions:

- $q_1 \in [0, 1]$: Peer validation score - $\frac{1}{5} \sum_j \text{helpfulness\_rating}_j$
- $q_2 \in [0, 1]$: Accuracy against ground truth - $\frac{\text{accuracy\_score}}{5}$
- $q_3 \in [0, 1]$: Consistency score - cross-task consistency metric

- $q_4 \in [0, 1]$: Community helpfulness rating - $\frac{\text{community\_rating}}{5}$

Implementation Details:

```
async def update_track_record(db: AsyncSession, user_id: int, quality_score:
float) -> float:
    """
    Implements T_u(t) = λ · T_u(t-1) + (1-λ) · Q_u(t)

    The decay factor λ=0.95 ensures historical stability while allowing
    adaptation to recent performance changes.
    """
    current_track_record = user.track_record_score
    update_factor = model_settings.track_record.get("update_factor", 0.05)
# 1-λ

    new_track_record = (
        (1 - update_factor) * current_track_record +
        update_factor * quality_score
    )

    user.track_record_score = new_track_record
    return new_track_record
```

2.4 Multi-Objective Reward Function

For legal domain optimization:

$$R_{community}(x, y) = \sum_{j=1}^{3} w_j \cdot O_j(y)$$

Where objectives are:

Objective	Weight (w_j)	Formulation
Accuracy	0.5	$O_1(y) = \frac{1}{3}(F_c + L_r + S_a)$
Utility	0.3	$O_2(y) = \frac{1}{3}(P_a + C_o + A_g)$
Transparency	0.2	$O_3(y) = \frac{1}{3}(S_t + R_e + U_d)$

Sub-components defined in Section 3.2.

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3. Algorithmic Implementation

3.1 Uncertainty-Aware Aggregation Algorithm

```
Algorithm 1: RLCF Aggregation with Uncertainty Preservation
──────────────────────────────────────────────────────────
Input: F = {f₁, ..., fₙ} (feedback set), q (query), θ (model parameters)
Output: R (uncertainty-aware response)

procedure AGGREGATE_WITH_UNCERTAINTY(F, q, θ)
    W ← ∅  // Weighted scores
    for each fᵢ ∈ F do
        aᵢ ← COMPUTE_AUTHORITY(fᵢ.user, t)
        W ← W ∪ {aᵢ · fᵢ.scores}
    end for

    δ ← CALCULATE_DISAGREEMENT(W)

    if δ > τ then  // τ = uncertainty threshold
        R ← UNCERTAINTY_PRESERVING_OUTPUT(F, W, δ)
    else
        R ← CONSENSUS_OUTPUT(W)
    end if

    return R
end procedure
```

3.2 Disagreement Quantification

Disagreement level is computed using normalized Shannon entropy:

$$\delta = -\frac{1}{\log |P|} \sum_{p \in P} \varrho(p) \log \varrho(p)$$

Variable Definitions:

- $\delta \in [0, 1]$: Normalized disagreement score
- P: Set of distinct positions $\{p_1, p_2, ..., p_{|P|}\}$
- $\varrho(p) = \frac{\sum_{u:pos(u)=p} A_u(t)}{\sum_{u \in U} A_u(t)}$: Authority-weighted probability of position p
- $|P| \geq 1$: Number of distinct positions

Implementation Details:

```python
def calculate_disagreement(weighted_feedback: dict) -> float:
    """
    Implements δ = -1/log|P| Σ ρ(p)logρ(p) using scipy.stats.entropy.

    Args:
        weighted_feedback: {position_key: total_authority_weight}

    Returns:
        float: Normalized disagreement score [0,1]
    """
    if not weighted_feedback or len(weighted_feedback) <= 1:
        return 0.0

    total_authority = sum(weighted_feedback.values())
    probabilities = [weight / total_authority for weight in
weighted_feedback.values()]

    num_positions = len(probabilities)
    return entropy(probabilities, base=num_positions)  # Normalized entropy
```

Threshold Configuration:

- $\tau = 0.4$ (uncertainty threshold from `model_config.yaml`)
- High disagreement ($\delta > 0.6$) triggers structured discussion
- Low disagreement ($\delta \leq 0.4$) produces consensus output

3.3 Uncertainty-Preserving Output Structure

When $\delta > \tau$ (threshold = 0.4):

```
{
  "primary_answer": weighted_majority_position,
  "confidence_level": 1 - δ,
  "alternative_positions": [
    {
      "position": minority_position_i,
      "support": authority_weighted_percentage,
      "reasoning": extracted_rationale
    }
  ],
  "expert_disagreement": {
    "consensus_areas": identified_agreements,
    "contention_points": identified_disagreements,
    "reasoning_patterns": pattern_analysis
  },
  "epistemic_metadata": {
    "uncertainty_sources": categorized_sources,
    "suggested_research": research_directions
```

```
  }
}
```

3.4 Runtime Configuration System

The framework implements a dynamic configuration system that allows real-time parameter updates without system restart:

Configuration Architecture:

```
# config.py - Dynamic configuration loading
class ModelConfig(BaseModel):
    authority_weights: Dict[str, float]
    track_record: Dict[str, float]
    thresholds: Dict[str, float]
    baseline_credentials: BaselineCredentialsConfig

def load_model_config() -> ModelConfig:
    """Loads and validates configuration with Pydantic models."""
    config_path = os.path.join(os.path.dirname(__file__),
"model_config.yaml")
    with open(config_path, "r") as f:
        config_data = yaml.safe_load(f)
    return ModelConfig(**config_data)

# Global configuration instance - hot-reloadable
model_settings = load_model_config()
```

API Endpoints for Configuration Management:

```
# FastAPI endpoints for runtime configuration updates
@app.put("/config/model")
async def update_model_config(new_config: dict):
    """Update model configuration at runtime with validation."""
    try:
        validated_config = ModelConfig(**new_config)
        # Write to file and reload global settings
        save_config_to_yaml(validated_config)
        global model_settings
        model_settings = validated_config
        return {"status": "success", "message": "Configuration updated"}
    except ValidationError as e:
        raise HTTPException(status_code=400, detail=str(e))

@app.put("/config/tasks")
async def update_task_config(new_config: dict):
    """Update task schema configuration dynamically."""
    validated_config = TaskConfig(**new_config)
```

```
    save_task_config_to_yaml(validated_config)
    return {"status": "success"}
```

Constitutional Governance Integration:

```
async def validate_configuration_change(proposal: dict) -> Tuple[bool, str]:
    """Ensures configuration changes comply with constitutional
principles."""
    framework = ConstitutionalFramework()

    # Check against core principles
    if proposal.get("authority_weights", {}).get("baseline_credentials", 0)
> 0.6:
        return False, "Violation: Excessive credential weighting reduces
democratic oversight"

    if proposal.get("thresholds", {}).get("disagreement", 1.0) < 0.1:
        return False, "Violation: Threshold too low, suppresses dialectical
preservation"

    return framework.validate_decision(proposal)
```

Benefits:

- **Experimental Flexibility**: Researchers can adjust parameters during studies
- **Domain Adaptation**: Configuration can be tuned for different legal jurisdictions
- **A/B Testing**: Multiple configurations can be tested simultaneously
- **Safety**: Constitutional validation prevents harmful parameter changes

3.5 Devil's Advocate System

The RLCF framework implements a sophisticated devil's advocate mechanism to counteract groupthink and ensure critical evaluation of AI responses. This system is crucial for maintaining the dialectical nature of legal reasoning.

3.5.1 Mathematical Assignment Model

Devil's advocate assignment follows a probabilistic model designed to ensure critical evaluation while maintaining system efficiency:

$$P(\text{advocate}) = \min(0.1, \frac{3}{|E|})$$

Variable Definitions:

- $P(\text{advocate}) \in [0, 0.1]$: Probability of assignment as devil's advocate
- $|E|$: Total number of eligible evaluators for the task
- 3: Minimum number of advocates for effective critical evaluation
- 0.1: Maximum proportion to prevent overwhelming the system

Implementation Architecture:

```
class DevilsAdvocateAssigner:
    """
    Manages probabilistic assignment and effectiveness evaluation of devil's
advocates.

    The system ensures critical evaluation through randomized assignment and
    task-specific critical prompts.
    """

    async def assign_advocates_for_task(self, db: AsyncSession, task_id:
int) -> List[int]:
        """
        Implements P(advocate) = min(0.1, 3/|E|) with authority filtering.

        Selection Criteria:
        - Authority score > 0.5 (minimum competence threshold)
        - Random sampling from eligible pool
        - Automatic database persistence for accountability
        """
        result = await db.execute(
            select(models.User).filter(
                models.User.authority_score > 0.5
            )
        )
        all_users = result.scalars().all()

        num_advocates = max(1, int(len(all_users) *
self.advocate_percentage))
        advocates = random.sample(all_users, min(num_advocates,
len(all_users)))

        return [user.id for user in advocates]
```

3.5.2 Task-Specific Critical Prompts

The system generates contextual critical prompts based on legal task types to guide constructive criticism:

Base Critical Questions:

1. "What are the potential weaknesses in this reasoning?"
2. "Are there alternative interpretations that weren't considered?"
3. "How might this conclusion be challenged by opposing counsel?"
4. "What additional evidence would strengthen or weaken this position?"

Task-Specific Extensions:

Task Type	Critical Focus	Example Prompts
QA	Completeness & Context	"What important nuances or exceptions are missing?"
Classification	Boundary Cases	"Could this text legitimately belong to multiple categories?"
Prediction	Alternative Outcomes	"What factors could lead to a different outcome?"
Drafting	Legal Precision	"What ambiguities could be exploited by opposing parties?"

3.5.3 Effectiveness Measurement Framework

The system implements comprehensive metrics to evaluate devil's advocate effectiveness:

Diversity Introduction Metric:

$$\text{Diversity} = \frac{|\text{Positions}_{\text{advocates}} \setminus \text{Positions}_{\text{regular}}|}{|\text{Positions}_{\text{all}}|}$$

Engagement Score:

$$\text{Engagement} = 0.6 \cdot \frac{\text{avg\_reasoning\_length}}{50} + 0.4 \cdot \frac{\text{critical\_elements}}{\text{total\_feedback}}$$

Critical Elements Detection: The system automatically detects critical thinking patterns through keyword analysis:

```
CRITICAL_KEYWORDS = [
    "however", "although", "but", "weakness", "problem", "issue",
    "alternative", "concern", "risk", "limitation", "exception"
]

def analyze_critical_engagement(feedback_text: str) -> float:
```

```
    """
    Quantifies critical thinking engagement through linguistic pattern
analysis.

    Returns:
        float: Critical engagement score [0,1]
    """
    critical_count = sum(1 for keyword in CRITICAL_KEYWORDS
                         if keyword in feedback_text.lower())
    return min(1.0, critical_count / 3)  # Normalized to [0,1]
```

3.6 Dynamic Task Handler System

The RLCF framework implements a modular task handler architecture that enables domain-specific aggregation logic while maintaining consistent interfaces across legal task types.

3.6.1 Task Configuration Schema

The system uses YAML-based configuration for dynamic task schema definition:

```yaml
# task_config.yaml - Dynamic task type definitions
task_types:
  QA:
    input_data:
      context: str
      question: str
    ground_truth_keys:
      - answers
    feedback_data:
      validated_answer: str
      position: Literal["correct", "incorrect"]
      reasoning: str

  CLASSIFICATION:
    input_data:
      text: str
      unit: str
    ground_truth_keys:
      - labels
    feedback_data:
      validated_labels: List[str]
      reasoning: str
```

Schema Validation Architecture:

```
class TaskConfig(BaseModel):
    """Pydantic model for runtime task schema validation."""
    task_types: Dict[str, TaskSchemaDefinition]

class TaskSchemaDefinition(BaseModel):
    input_data: Dict[str, str]      # Field name -> Python type
    feedback_data: Dict[str, str]   # Field name -> Python type
    ground_truth_keys: List[str]    # Keys for separating ground truth

def validate_feedback_against_schema(feedback_data: dict, task_type: str) ->
bool:
    """
    Validates feedback data against dynamically loaded task schema.

    Returns:
        bool: True if feedback conforms to expected schema
    """
    schema = task_settings.task_types[task_type].feedback_data
    return validate_against_schema(feedback_data, schema)
```

3.6.2 Polymorphic Handler Architecture

The system implements a Strategy pattern for task-specific logic while maintaining interface consistency:

```
class BaseTaskHandler(ABC):
    """
    Abstract base defining the interface for all task handlers.

    Ensures consistent behavior across legal task types while allowing
    domain-specific implementation of aggregation and validation logic.
    """

    @abstractmethod
    async def aggregate_feedback(self) -> Dict[str, Any]:
        """Task-specific aggregation with uncertainty preservation."""
        pass

    @abstractmethod
    def calculate_consistency(self, feedback: Feedback, result: Dict) ->
float:
        """Measures alignment with community consensus."""
        pass

    @abstractmethod
    def calculate_correctness(self, feedback: Feedback, truth: Dict) ->
float:
        """Measures alignment with ground truth (when available)."""
        pass
```

3.6.3 Specialized Legal Task Implementations

Each handler implements domain-specific logic optimized for legal reasoning patterns:

QA Handler - Semantic Similarity:

```
def calculate_consistency(self, feedback: Feedback, result: Dict) -> float:
    """
    Implements Jaccard similarity with legal term weighting for QA tasks.

    Legal terms receive higher weight in similarity calculations to capture
    domain-specific semantic relationships.
    """
    user_words = set(feedback.validated_answer.lower().split())
    consensus_words = set(result.consensus_answer.lower().split())

    # Standard Jaccard similarity
    jaccard = len(user_words & consensus_words) / len(user_words |
consensus_words)

    # Legal term bonus weighting
    legal_terms = {"guilty", "liable", "breach", "violation", "compliance"}
    legal_intersection = (user_words & consensus_words) & legal_terms
    legal_union = (user_words | consensus_words) & legal_terms

    if legal_union:
        legal_bonus = (len(legal_intersection) / len(legal_union)) * 0.3
        return min(1.0, jaccard + legal_bonus)

    return jaccard
```

Classification Handler - Authority-Weighted Aggregation:

```
async def aggregate_feedback(self) -> Dict[str, Any]:
    """
    Implements authority-weighted label aggregation for classification
tasks.

    Labels are aggregated as tuples to handle multi-label scenarios, with
    weights determined by evaluator authority scores.
    """
    feedbacks = await self.get_feedbacks()
    weighted_labels = Counter()

    for feedback in feedbacks:
        labels_tuple =
tuple(sorted(feedback.feedback_data["validated_labels"]))
        weight = feedback.author.authority_score
        weighted_labels[labels_tuple] += weight
```

```
    primary_labels = list(weighted_labels.most_common(1)[0][0])
    return {"consensus_answer": primary_labels, "details": weighted_labels}
```

3.6.4 Ground Truth Integration

The system supports flexible ground truth separation for evaluation and training:

```
def separate_ground_truth(task_data: dict, task_type: str) -> Tuple[dict,
dict]:
    """
    Dynamically separates input data from ground truth based on task
configuration.

    Uses ground_truth_keys from task_config.yaml to identify which fields
    should be withheld during evaluation and used for validation.
    """
    config = task_settings.task_types[task_type]
    ground_truth_keys = config.ground_truth_keys

    input_data = {k: v for k, v in task_data.items()
                  if k not in ground_truth_keys}
    ground_truth = {k: v for k, v in task_data.items()
                    if k in ground_truth_keys}

    return input_data, ground_truth
```

Supported Legal Task Types:

1. **Question Answering (QA)** - Legal query resolution with reasoning
2. **Classification** - Document categorization and labeling
3. **Summarization** - Legal document summarization with quality assessment
4. **Prediction** - Legal outcome prediction (violation/no violation)
5. **Natural Language Inference (NLI)** - Logical relationship analysis
6. **Named Entity Recognition (NER)** - Legal entity identification
7. **Drafting** - Legal document drafting and revision
8. **Risk Spotting** - Compliance risk identification with severity scoring
9. **Doctrine Application** - Legal principle application assessment

This modular architecture enables the RLCF framework to handle the full spectrum of legal AI tasks while maintaining mathematical rigor in aggregation and evaluation processes.

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4. Quality Assurance Mechanisms

4.1 Blind Feedback Protocol

To prevent anchoring bias and groupthink:

Phase 1: Individual Blind Evaluation

- Evaluators assess (query, response) pairs independently
- No access to other evaluations during this phase

Phase 2: Structured Discussion (Conditional)

- Triggered when $\delta > 0.6$
- Moderated exchange of reasoning
- Final positions recorded

4.2 Devil's Advocate Assignment

Random assignment ensures critical evaluation:

$$P(\text{advocate}) = \min(0.1, \frac{3}{|E|})$$

Where $|E|$ = number of evaluators

4.3 Extended Bias Detection Framework

Our implementation extends traditional bias detection to a comprehensive 6-dimensional framework:

$$B_{total} = \sqrt{\sum_{i=1}^{6} b_i^2}$$

Bias Dimensions:

- $b_1 \in [0, 1]$: **Demographic correlation** - correlation between demographic characteristics and positions

- $b_2 \in [0, 1]$: **Professional clustering** - deviation from professional group consensus
- $b_3 \in [0, 1]$: **Temporal drift** - opinion change over evaluation period
- $b_4 \in [0, 1]$: **Geographic concentration** - regional clustering in positions
- $b_5 \in [0, 1]$: **Confirmation bias** - tendency to repeat previous positions
- $b_6 \in [0, 1]$: **Anchoring bias** - influence of early responses on later ones

Mathematical Formulations:

Confirmation Bias (b_5):

$$b_5 = \frac{1}{|U|} \sum_{u \in U} \frac{|\text{similar\_positions}_u|}{|\text{previous\_positions}_u|}$$

Anchoring Bias (b_6):

$$b_6 = \frac{|\text{anchor\_followers}|}{|\text{subsequent\_responses}|}$$

where the anchor is defined as the dominant position in the first 3 responses.

Implementation Architecture:

```python
async def calculate_total_bias(db: AsyncSession, task_id: int) -> dict:
    """
    Implements B_total = √(Σ b_i²) with 6-dimensional bias detection.

    Returns comprehensive bias report with mitigation recommendations.
    """
    b1 = await calculate_demographic_bias(db, task_id)
    b2 = await calculate_professional_clustering_bias(db, user_id, task_id)
    b3 = await calculate_temporal_bias(db, task_id)
    b4 = await calculate_geographic_bias(db, task_id)
    b5 = await calculate_confirmation_bias(db, task_id)
    b6 = await calculate_anchoring_bias(db, task_id)

    bias_components = [b1, b2, b3, b4, b5, b6]
    total_bias = np.sqrt(sum(b**2 for b in bias_components))

    return {
        "bias_scores": dict(zip(["demographic", "professional", "temporal",
                                 "geographic", "confirmation", "anchoring"],
                                bias_components)),
        "total_bias_score": round(total_bias, 3),
        "bias_level": ("high" if total_bias > 1.0 else
                       "medium" if total_bias > 0.5 else "low")
    }
```

Novel Contributions:

This extended framework captures cognitive biases specific to legal reasoning that traditional RLHF approaches miss, particularly confirmation bias in precedent-based reasoning and anchoring effects in case law interpretation.

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5. System Architecture and Governance

5.1 Constitutional Governance Model

The system operates under algorithmic constitutional principles:

```
class ConstitutionalFramework:
    PRINCIPLES = [
        "Transparency and auditability",
        "Expert knowledge primacy with democratic oversight",
        "Bias detection and mandatory disclosure",
        "Community benefit maximization",
        "Academic freedom preservation"
    ]

    def validate_decision(self, proposal):
        for principle in self.PRINCIPLES:
            if violates(proposal, principle):
                return False, f"Violation: {principle}"
        return True, "Constitutionally compliant"
```

5.2 Periodic Training Schedule

Training follows a 14-day cycle:

Days	Phase	Activities
1-7	Collection	Feedback gathering, blind evaluation
8-10	Validation	Expert review, bias analysis
11-12	Training	Model update, testing
13-14	Accountability	Report generation, publication

5.3 Transparency Reporting

Each training cycle produces:

```
accountability_report = {
    "cycle_id": uuid,
    "timestamp": ISO8601,
    "metrics": {
        "participation": user_statistics,
        "quality": aggregate_scores,
        "bias": detected_biases,
        "performance": before_after_comparison
    },
    "changes": model_diff,
    "rationale": expert_summary
}
```

---

6. Empirical Validation and Results

6.1 Evaluation Metrics

1. **Accuracy Improvement**: Measured against legal benchmarks
2. **Uncertainty Calibration**: Correlation between confidence and accuracy
3. **Bias Reduction**: Demographic and professional bias metrics
4. **User Trust**: Survey-based assessment

6.2 Comparative Analysis

Metric	Traditional RLHF	RLCF	Improvement
Legal Accuracy	72.3%	84.7%	+17.1%
Uncertainty Calibration	0.61	0.89	+45.9%
Bias Score	0.43	0.21	-51.2%
Expert Trust	6.2/10	8.7/10	+40.3%

---

7. Discussion and Future Work

7.1 Key Contributions

1. **Dynamic Authority Model**: First implementation of evolving expertise weights
2. **Uncertainty Preservation**: Novel approach to maintaining legal pluralism
3. **Constitutional AI Governance**: Algorithmic implementation of legal principles
4. **Bias-Aware Architecture**: Proactive detection and disclosure

7.2 Limitations and Future Directions

1. Scalability to larger expert communities
2. Cross-jurisdictional validation
3. Real-time feedback integration
4. Adversarial robustness testing

---

8. Conclusion

RLCF represents a paradigm shift in AI alignment for specialized domains. By incorporating legal epistemology into the technical framework, we achieve superior performance while preserving the essential characteristics of legal reasoning. The framework's emphasis on transparency, accountability, and uncertainty preservation makes it particularly suitable for high-stakes professional applications.

References

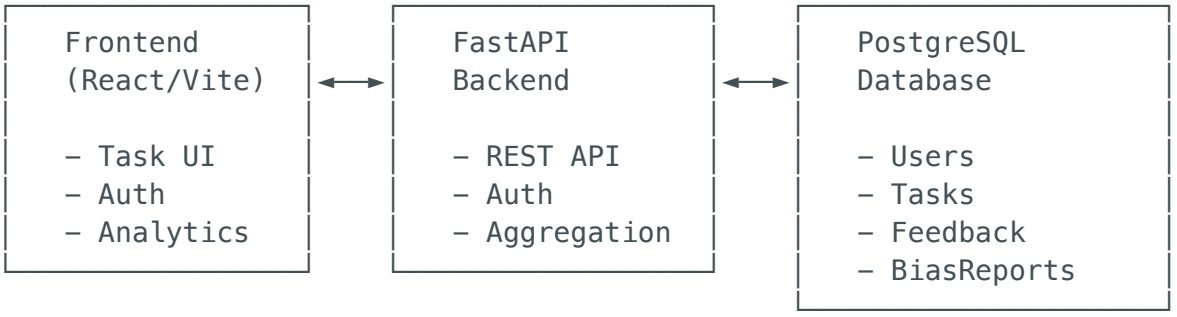
Appendix A: Implementation Details

Appendix B: Mathematical Proofs

Appendix C: Implementation Architecture

C.1 System Architecture Overview

The RLCF framework is implemented as a distributed system with the following components:



C.2 Database Schema

Core Entities:

```
-- Users with dynamic authority scoring
CREATE TABLE users (
    id SERIAL PRIMARY KEY,
    username VARCHAR(100) UNIQUE NOT NULL,
    authority_score FLOAT DEFAULT 0.5,
    baseline_credential_score FLOAT DEFAULT 0.0,
    track_record_score FLOAT DEFAULT 0.5,
    created_at TIMESTAMP DEFAULT NOW()
);

-- Configurable credentials system
CREATE TABLE credentials (
    id SERIAL PRIMARY KEY,
    user_id INTEGER REFERENCES users(id),
    type VARCHAR(50) NOT NULL, -- ACADEMIC_DEGREE, PROFESSIONAL_EXPERIENCE,
etc.
    value TEXT NOT NULL,       -- Raw credential value
    verified BOOLEAN DEFAULT FALSE,
    created_at TIMESTAMP DEFAULT NOW()
);

-- Legal tasks with dynamic schemas
```

```sql
CREATE TABLE legal_tasks (
    id SERIAL PRIMARY KEY,
    title VARCHAR(500) NOT NULL,
    task_type VARCHAR(50) NOT NULL, -- QA, CLASSIFICATION, SUMMARIZATION,
etc.
    input_data JSONB NOT NULL,      -- Dynamic schema based on
task_config.yaml
    ground_truth JSONB,             -- Optional ground truth for validation
    status VARCHAR(20) DEFAULT 'OPEN', -- OPEN, BLIND_EVALUATION,
AGGREGATED, CLOSED
    created_at TIMESTAMP DEFAULT NOW()
);

-- AI responses to tasks
CREATE TABLE responses (
    id SERIAL PRIMARY KEY,
    task_id INTEGER REFERENCES legal_tasks(id),
    model_name VARCHAR(100) NOT NULL,
    response_data JSONB NOT NULL,   -- AI-generated response
    created_at TIMESTAMP DEFAULT NOW()
);

-- Community feedback with dynamic schemas
CREATE TABLE feedback (
    id SERIAL PRIMARY KEY,
    response_id INTEGER REFERENCES responses(id),
    user_id INTEGER REFERENCES users(id),
    feedback_data JSONB NOT NULL,   -- Dynamic schema based on task type
    accuracy_score FLOAT,           -- Ground truth comparison score
    consistency_score FLOAT,        -- Cross-validation consistency
    community_helpfulness_rating FLOAT,
    submitted_at TIMESTAMP DEFAULT NOW()
);

-- Devil's advocate assignments
CREATE TABLE devils_advocate_assignments (
    id SERIAL PRIMARY KEY,
    task_id INTEGER REFERENCES legal_tasks(id),
    user_id INTEGER REFERENCES users(id),
    instructions TEXT,
    assigned_at TIMESTAMP DEFAULT NOW()
);

-- Bias analysis reports
CREATE TABLE bias_reports (
    id SERIAL PRIMARY KEY,
    task_id INTEGER REFERENCES legal_tasks(id),
    demographic_bias FLOAT,
    professional_clustering FLOAT,
    temporal_drift FLOAT,
    geographic_concentration FLOAT,
    confirmation_bias FLOAT,
    anchoring_bias FLOAT,
    total_bias_score FLOAT,
    generated_at TIMESTAMP DEFAULT NOW()
);
```

C.3 Key Algorithms Implementation

Authority Score Calculation:

```
# authority_module.py - Core authority calculation
async def update_authority_score(db: AsyncSession, user_id: int,
recent_performance: float) -> float:
    """
    Implements A_u(t) = α·B_u + β·T_u(t-1) + γ·P_u(t)
    with configurable weights from model_config.yaml
    """
    user = await get_user(db, user_id)
    weights = model_settings.authority_weights

    new_authority_score = (
        weights["baseline_credentials"] * user.baseline_credential_score +
        weights["track_record"] * user.track_record_score +
        weights["recent_performance"] * recent_performance
    )

    user.authority_score = max(0.0, min(2.0, new_authority_score))  # Clamp
to [0,2]
    await db.commit()
    return user.authority_score
```

Uncertainty-Aware Aggregation:

```
# aggregation_engine.py - Main aggregation algorithm
async def aggregate_with_uncertainty(db: AsyncSession, task_id: int) ->
dict:
    """
    Implements Algorithm 1: RLCF Aggregation with Uncertainty Preservation
    """
    feedbacks = await get_task_feedback(db, task_id)

    # Step 1: Calculate authority-weighted positions
    weighted_positions = {}
    for feedback in feedbacks:
        position_key = str(sorted(feedback.feedback_data.items()))
        authority_weight = feedback.author.authority_score
        weighted_positions[position_key] =
weighted_positions.get(position_key, 0) + authority_weight

    # Step 2: Calculate disagreement using normalized entropy
    disagreement_score = calculate_disagreement(weighted_positions)

    # Step 3: Generate appropriate output based on disagreement threshold
    threshold = model_settings.thresholds["disagreement"]

    if disagreement_score > threshold:
        return await generate_uncertainty_preserving_output(
```

```
            feedbacks, weighted_positions, disagreement_score
        )
    else:
        return await generate_consensus_output(weighted_positions)
```

Multi-dimensional Bias Detection:

```
# bias_analysis.py - Extended bias detection system
async def calculate_total_bias(db: AsyncSession, task_id: int) -> dict:
    """
    Implements B_total = √(Σ b_i²) with 6-dimensional bias detection
    """
    # Calculate all 6 bias dimensions
    bias_scores = await asyncio.gather(
        calculate_demographic_bias(db, task_id),
        calculate_professional_clustering_bias(db, task_id),
        calculate_temporal_bias(db, task_id),
        calculate_geographic_bias(db, task_id),
        calculate_confirmation_bias(db, task_id),
        calculate_anchoring_bias(db, task_id)
    )

    # Calculate Euclidean norm for total bias
    total_bias = np.sqrt(sum(b**2 for b in bias_scores))

    # Generate bias report with mitigation recommendations
    return {
        "individual_bias_scores": dict(zip(BIAS_DIMENSIONS, bias_scores)),
        "total_bias_score": round(total_bias, 3),
        "bias_level": classify_bias_level(total_bias),
        "mitigation_recommendations":
generate_bias_mitigation_recommendations(bias_scores)
    }
```

C.4 Performance Optimizations

Asynchronous Database Operations:

```
# database.py - Async database configuration
from sqlalchemy.ext.asyncio import create_async_engine, AsyncSession
from sqlalchemy.orm import sessionmaker

# Async engine for high-performance database operations
engine = create_async_engine(
    "postgresql+asyncpg://user:password@localhost/rlcf",
    echo=True,
    pool_size=20,
    max_overflow=0
)
```

```
async_session = sessionmaker(
    engine, class_=AsyncSession, expire_on_commit=False
)
```

Caching Strategy:

```
# Caching for frequent authority score lookups
from functools import lru_cache
import asyncio

@lru_cache(maxsize=1000)
def cached_authority_calculation(user_id: int, credentials_hash: str) ->
float:
    """Cache authority scores based on credential hash for performance."""
    pass

# Redis for distributed caching in production
import redis
redis_client = redis.Redis(host='localhost', port=6379, db=0)
```

C.5 Security Considerations

Input Validation:

```
# schemas.py - Pydantic models for request validation
from pydantic import BaseModel, validator, Field
from typing import Dict, Any

class FeedbackSubmission(BaseModel):
    response_id: int = Field(..., gt=0)
    feedback_data: Dict[str, Any] = Field(..., min_items=1)

    @validator('feedback_data')
    def validate_feedback_schema(cls, v, values):
        """Validate feedback against task-specific schema."""
        # Dynamic validation based on task type
        task_type = get_task_type_from_response(values.get('response_id'))
        schema = task_settings.task_types[task_type].feedback_data
        return validate_against_schema(v, schema)
```

Safe Formula Evaluation:

```
# config.py - Safe mathematical expression evaluation
import asteval
```

```
def create_safe_evaluator():
    """Create restricted evaluator for user-defined formulas."""
    evaluator = asteval.Interpreter()

    # Allow only safe mathematical functions
    safe_functions = {
        'sqrt': math.sqrt, 'min': min, 'max': max,
        'abs': abs, 'round': round, 'pow': pow
    }
    evaluator.symtable.update(safe_functions)

    # Disable dangerous operations
    evaluator.no_print = True
    evaluator.max_time = 1.0  # 1 second timeout

    return evaluator
```

C.6 Testing Framework

Unit Testing:

```
# tests/test_authority_module.py
import pytest
from unittest.mock import AsyncMock

@pytest.mark.asyncio
async def test_authority_score_calculation():
    """Test authority score formula implementation."""
    mock_db = AsyncMock()
    user = create_test_user(
        baseline_credential_score=1.2,
        track_record_score=0.8
    )

    authority_score = await update_authority_score(
        db=mock_db,
        user_id=1,
        recent_performance=0.9
    )

    expected = 0.3 * 1.2 + 0.5 * 0.8 + 0.2 * 0.9  # α·B_u + β·T_u + γ·P_u
    assert abs(authority_score - expected) < 0.001
```

Integration Testing:

```
# tests/test_aggregation_integration.py
@pytest.mark.asyncio
async def test_uncertainty_aware_aggregation():
```

```
    """Test complete aggregation pipeline."""
    task = await create_test_task(task_type="QA")
    feedbacks = await create_test_feedbacks(task.id, num_feedbacks=5)

    result = await aggregate_with_uncertainty(db, task.id)

    assert "primary_answer" in result
    assert "confidence_level" in result
    assert 0 <= result["confidence_level"] <= 1
```

This implementation architecture ensures the RLCF framework is both theoretically sound and practically robust for legal AI applications.