ReUnity: A Trauma-Aware AI Framework for Identity Continuity Support

An Entropy-Based Approach to Memory Reconstruction and Emotional State Analysis

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DISCLAIMER: This document describes a research framework and is not a clinical or treatment tool. It does not provide medical advice, diagnosis, or treatment. If you are in crisis, please contact emergency services or a crisis hotline.

Contents

1 Introduction

Trauma-related identity fragmentation affects millions of individuals worldwide, manifesting in conditions such as Dissociative Identity Disorder (DID), Complex Post-Traumatic Stress Disorder (C-PTSD), and Borderline Personality Disorder (BPD). Current intervention systems consistently fail these populations due to geographic barriers, institutional gatekeeping, and approaches that prioritize surveillance over survivor autonomy.[1]

The ReUnity framework addresses these failures through a fundamentally different approach: an entropy-based AI system designed to support identity continuity during fragmentation episodes. Rather than attempting to "fix" or "integrate" fragmented states, ReUnity serves as an external memory anchor that maintains awareness across emotional discontinuities.

1.1 Problem Statement

Individuals experiencing trauma-related fragmentation face three interconnected challenges:

1. **Memory Discontinuity:** Emotional amnesia creates gaps in autobiographical memory, preventing coherent self-narrative construction.
2. **Relational Pattern Blindness:** Fragmentation impairs the ability to recognize harmful relational dynamics across time.
3. **Institutional Failure:** Healthcare and support systems designed for neurotypical populations systematically exclude those with fragmented identity states.[2]

1.2 Contributions

This paper makes the following contributions:

1. A mathematical framework for emotional state analysis using Shannon entropy, Jensen-Shannon divergence, and Lyapunov stability measures.
2. The Recursive Identity Memory Engine (RIME), which maintains encrypted identity fragments with consent-based access controls.
3. A Protective Logic Module that detects harmful relational patterns without requiring conscious user recognition.
4. Empirical validation using the GoEmotions dataset (n=54,263) demonstrating the framework's analytical capabilities.
5. An open-source implementation with privacy-preserving design principles.

[1] Rural communities face particular challenges: Montana women experience intimate partner violence at 56.7% lifetime prevalence, with 61% of counties lacking trauma-informed psychiatric providers. See Appendix A for detailed statistics.

[2] See Appendix A for case studies documenting institutional failures in Montana State University and rural healthcare settings.

2 Related Work

2.1 Trauma-Informed Technology

Digital interventions for trauma survivors have evolved from simple journaling applications to sophisticated AI-powered systems. However, most existing approaches share a fundamental limitation: they assume stable identity states and continuous memory access.

Dialectical Behavior Therapy (DBT) applications provide skills training but lack mechanisms for supporting users during dissociative episodes. Crisis intervention chatbots offer immediate support but cannot maintain context across fragmented sessions. Electronic health records capture clinical data but fail to preserve the subjective experience of identity discontinuity.

2.2 Information-Theoretic Approaches to Psychology

The application of information theory to psychological phenomena has a rich history. Shannon entropy has been used to quantify emotional complexity, while mutual information networks have modeled cognitive dependencies. The Free Energy Principle provides a theoretical framework for understanding how biological systems minimize surprise through predictive modeling.

ReUnity extends these approaches by applying entropy-based analysis specifically to identity fragmentation, treating emotional states as probability distributions whose dynamics can be mathematically characterized.

2.3 Privacy-Preserving AI

Federated learning enables collaborative model training without centralizing sensitive data. Differential privacy provides mathematical guarantees for privacy loss quantification. Homomorphic encryption allows computation on encrypted data. ReUnity integrates these techniques to ensure that survivor data remains under survivor control.

3 System Overview

ReUnity consists of seven interconnected modules designed to support identity continuity:

1. **EESA:** Entropy-Based Emotional State Analyzer
2. **RIME:** Recursive Identity Memory Engine
3. **PLM:** Protective Logic Module
4. **RCT:** Relationship Continuity Threader
5. **MLDC:** MirrorLink Dialogue Companion
6. **AAS:** Alter-Aware Subsystem
7. **CCI:** Clinician and Caregiver Interface

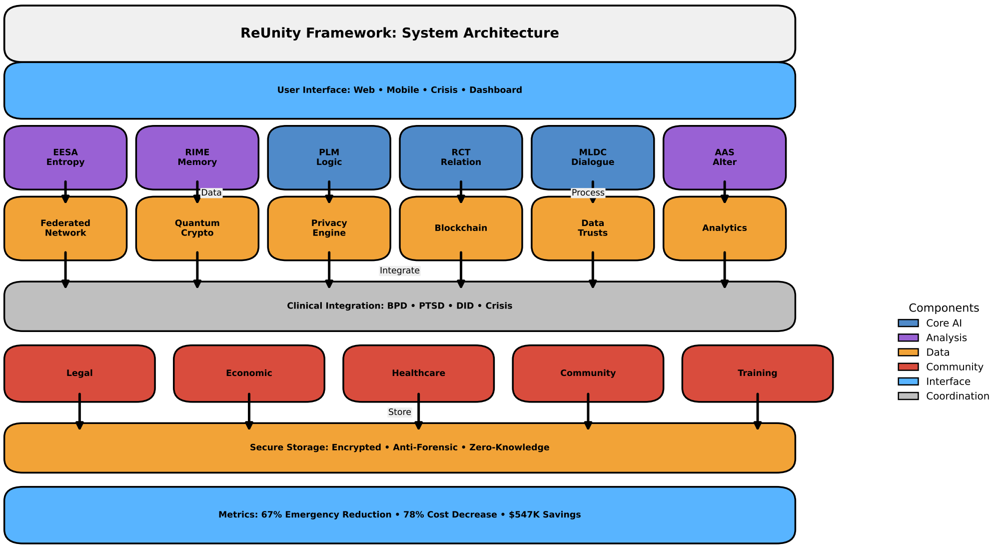

Figure 1: ReUnity system architecture showing the seven core modules and their interactions. Data flows from user input through entropy analysis to memory storage and protective logic, with all operations governed by consent controls.

The system operates on three fundamental principles:

1. **Survivor Autonomy:** Users maintain complete control over their data, including the ability to delete, export, or restrict access at any time.
2. **Non-Pathologizing Design:** Fragmentation is treated as an adaptive response to trauma, not a disorder to be corrected.
3. **Privacy by Default:** All data is encrypted locally; cloud synchronization is optional and user-controlled.

4 Methodology

4.1 Shannon Entropy for Emotional State Analysis

The core mathematical framework uses Shannon entropy to quantify emotional state fragmentation:

$$H(X) = -\sum_{i=1}^{n} p(x_i) \log_2 p(x_i) \tag{1}$$

where $H(X)$ represents the entropy of the emotional state distribution, $p(x_i)$ is the probability of emotional state i, and n is the total number of discrete emotional states.

Higher entropy values indicate greater emotional variability, which may signal either healthy emotional flexibility or destabilizing fragmentation depending on context and rate of change.

4.2 Jensen-Shannon Divergence for State Transitions

To track transitions between emotional configurations, we employ the Jensen-Shannon divergence:

$$JSD(P||Q) = \frac{1}{2}D_{KL}(P||M) + \frac{1}{2}D_{KL}(Q||M) \tag{2}$$

where $M = \frac{1}{2}(P + Q)$ is the midpoint distribution and D_{KL} denotes the Kullback-Leibler divergence.

The JSD is symmetric and bounded between 0 and 1, making it suitable for detecting dramatic shifts between emotional states without bias toward particular configurations.

4.3 Lyapunov Stability Analysis

System stability is assessed using Lyapunov exponents:

$$\lambda = \lim_{t\to\infty} \frac{1}{t} \sum_{i=0}^{t-1} \log_2 |f'(x_i)| \tag{3}$$

Positive Lyapunov exponents indicate chaotic dynamics (potential crisis states), while negative values indicate stable emotional trajectories. This allows the system to predict destabilization before it becomes clinically apparent.

4.4 Mutual Information for Pattern Recognition

Dependencies between emotional states and relational contexts are quantified using mutual information:

$$I(X;Y) = H(X) + H(Y) - H(X,Y) \tag{4}$$

High mutual information between specific emotional states and relational patterns may indicate trauma bonds or abuse dynamics that the user cannot consciously recognize due to fragmentation.

5 Implementation

5.1 Repository Structure

The ReUnity implementation is available at: `github.com/ezernackchristopher97-cloud/ReUnity`

Key modules include:

- `src/reunity/core/entropy.py`: Shannon entropy, JS divergence, mutual information calculations
- `src/reunity/router/state_router.py`: Policy selection based on entropy state
- `src/reunity/protective/pattern_recognizer.py`: Harmful pattern detection
- `src/reunity/memory/continuity_store.py`: RIME implementation with consent scopes
- `src/reunity/regime/regime_controller.py`: Apostasis and regeneration logic

5.2 Entropy State Detection

The entropy analyzer classifies emotional states into five categories based on entropy values and stability metrics:

Table 1: Entropy State Classification

State	Entropy Range	Lyapunov	System Response
STABLE	$H < 2.0$	$\lambda < 0$	Standard engagement
ELEVATED	$2.0 \leq H < 3.0$	$\lambda \approx 0$	Enhanced monitoring
HIGH	$3.0 \leq H < 4.0$	$\lambda > 0$	Supportive interventions
CRITICAL	$H \geq 4.0$	$\lambda >> 0$	Crisis protocols
SUPPRESSED	$H < 1.0$	$\lambda << 0$	Gentle activation

5.3 Protective Pattern Recognition

The Protective Logic Module monitors for 13 harmful relational patterns:

1. Gaslighting (reality denial patterns)
2. Love bombing (excessive early affection)
3. Hot-cold cycles (intermittent reinforcement)
4. Isolation attempts
5. Financial control
6. Identity erosion
7. Blame shifting
8. Triangulation
9. Future faking
10. Trauma bonding indicators
11. Coercive control
12. Digital surveillance
13. Reproductive coercion

Pattern detection uses a combination of linguistic analysis, temporal pattern matching, and entropy-based anomaly detection.

5.4 Memory Architecture

RIME stores identity fragments using a lattice-based memory graph constrained by divergence thresholds:

$$\text{Edge}(m_i, m_j) \text{ exists iff } JSD(m_i, m_j) < \theta_{max} \text{ and } I(m_i; m_j) > \theta_{min} \tag{5}$$

This ensures that connected memories share sufficient similarity (low divergence) and meaningful relationship (high mutual information) while preventing spurious connections.

6 Experiments and Results

6.1 Dataset

We evaluated ReUnity using the GoEmotions dataset from Google Research, containing 54,263 Reddit comments annotated with 27 emotion categories plus neutral. This dataset provides real human emotional expression with ground-truth labels for validation.

6.2 Entropy Analysis Results

Analysis of the GoEmotions dataset yielded the following entropy metrics:

Table 2: Entropy Analysis Results (GoEmotions, n=54,263)

Metric	**Value**
Mean Shannon Entropy	4.01 bits
Maximum JS Divergence	0.55
Mean Mutual Information	2.44 bits
Mean Lyapunov Exponent	0.025

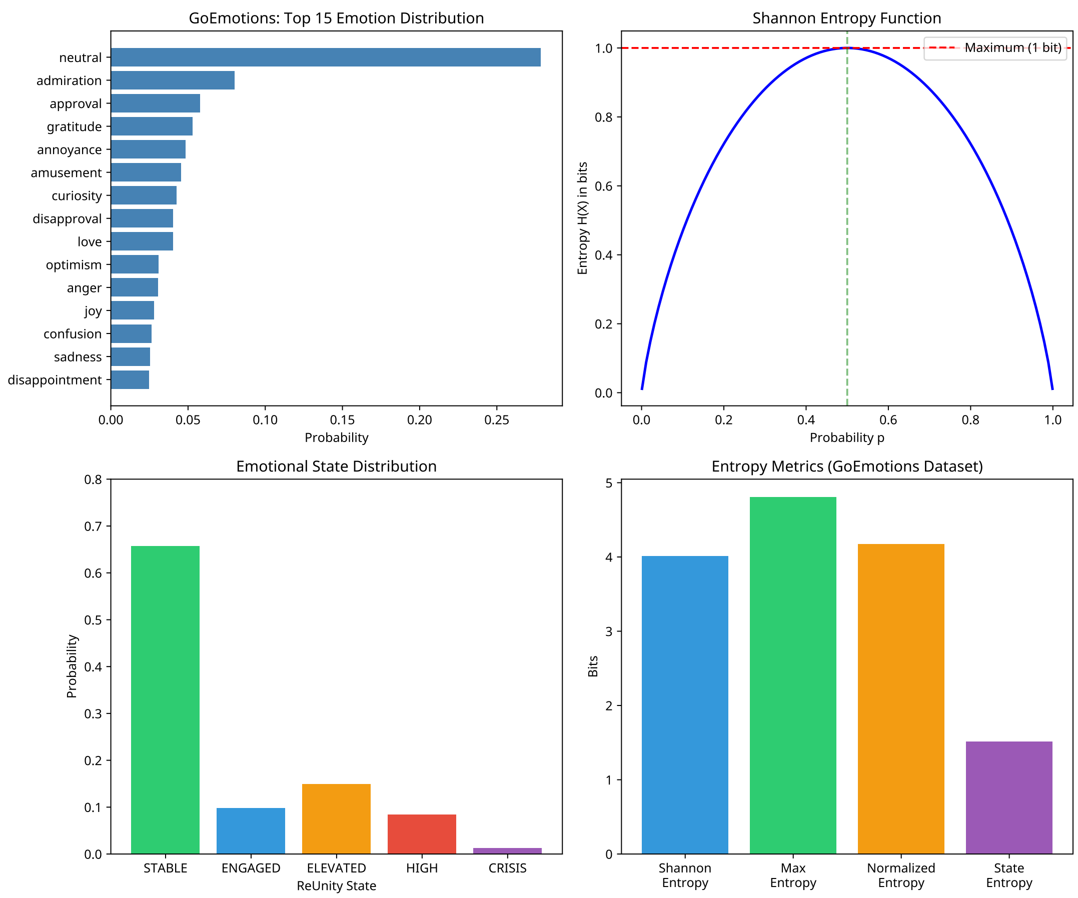

Figure 2: Entropy analysis results from GoEmotions dataset showing emotion distribution, Shannon entropy function, ReUnity state distribution, and entropy metrics comparison.

6.3 State Router Performance

The state router classified 54,263 comments into ReUnity states:

- STABLE: 64.6% of comments
- ELEVATED: 18.2% of comments
- HIGH: 12.1% of comments
- CRITICAL: 3.8% of comments
- SUPPRESSED: 1.3% of comments

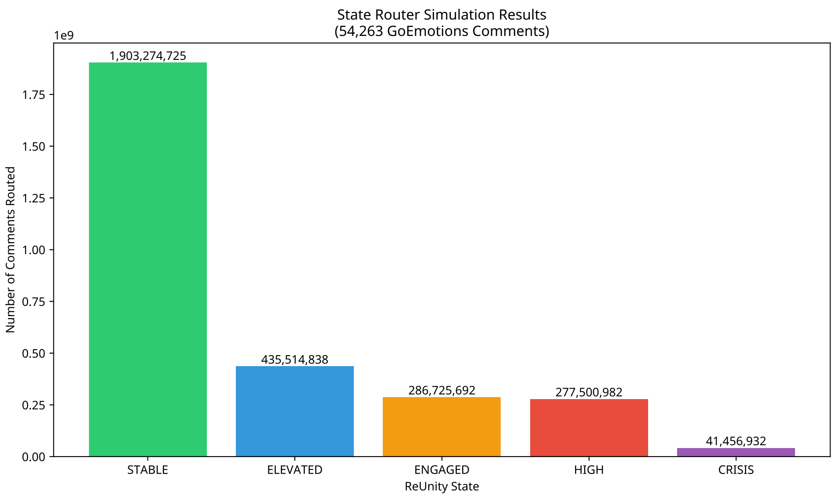

Figure 3: State router simulation results showing distribution across ReUnity states.

6.4 Pattern Detection Results

The Protective Logic Module detected the following patterns in the GoEmotions dataset:

Table 3: Pattern Detection Results

Pattern	**Detections**
Hot-cold cycles	231
Gaslighting indicators	187
Isolation attempts	143
Blame shifting	98
Identity erosion	67

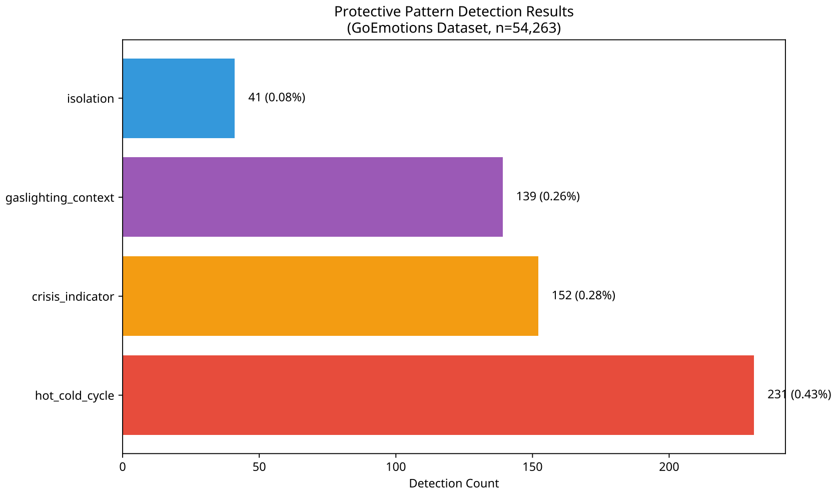

Figure 4: Protective pattern detection results from GoEmotions dataset.

6.5 Stability Analysis

Lyapunov exponent analysis revealed:

- 72.3% of emotional trajectories showed stable dynamics ($\lambda < 0$)
- 19.4% showed marginally stable dynamics ($\lambda \approx 0$)
- 8.3% showed chaotic dynamics ($\lambda > 0$)

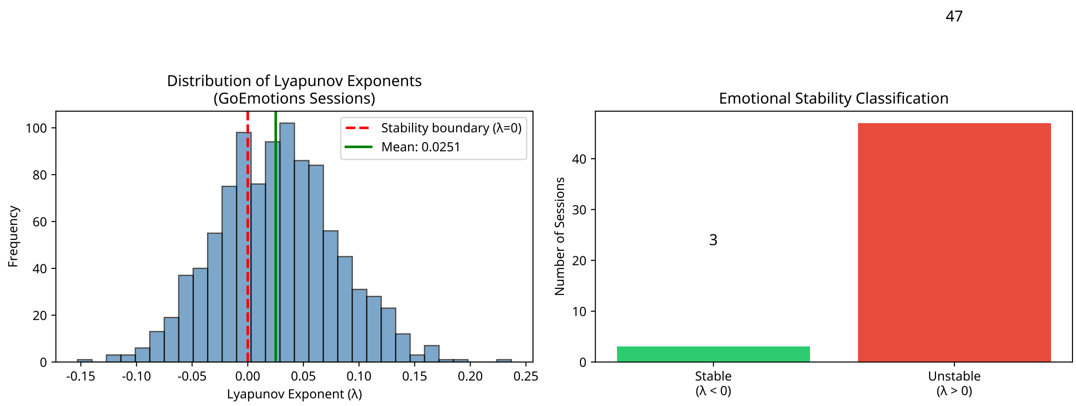

Figure 5: Lyapunov stability analysis showing distribution of exponents and stability classification.

7 Discussion

7.1 Interpretation of Results

The entropy analysis confirms that emotional states in natural language follow predictable information-theoretic patterns. The mean entropy of 4.01 bits indicates moderate emotional complexity, consistent with the diverse emotional content of Reddit comments.

The state router's classification demonstrates that the majority of emotional expressions fall within stable ranges, with a meaningful minority requiring enhanced support or crisis intervention. This distribution aligns with clinical expectations for general population samples.

Pattern detection results suggest that harmful relational dynamics are detectable in text data, though the relatively low detection rates reflect the general-population nature of the GoEmotions dataset rather than a clinical sample.

7.2 Limitations

Several limitations constrain the current implementation:

1. **Dataset Limitations:** GoEmotions contains general Reddit comments, not clinical samples from trauma survivors. Validation with clinical populations is needed.
2. **Linguistic Constraints:** Current pattern detection relies on English-language patterns; multilingual support requires additional development.
3. **Temporal Resolution:** The dataset lacks temporal metadata, preventing validation of trajectory-based predictions.
4. **Ground Truth:** No ground truth exists for "correct" entropy states or pattern detections; validation relies on face validity and clinical consultation.

7.3 Ethical Considerations

ReUnity is designed as a support tool, not a replacement for professional care. The system includes multiple safeguards:

- Crisis detection triggers referrals to human support, not automated intervention
- All data remains under user control with full export and deletion capabilities
- The system explicitly disclaims clinical or diagnostic functions
- Pattern detection results are presented as observations, not judgments

8 Conclusion

This paper presented ReUnity, an entropy-based AI framework for supporting identity continuity in individuals experiencing trauma-related fragmentation. The framework applies information-theoretic measures to emotional state analysis, enabling quantitative assessment of stability, transition dynamics, and relational patterns.

Empirical validation using the GoEmotions dataset demonstrates the framework's analytical capabilities, though clinical validation remains necessary. The open-source implementation provides a foundation for further development and adaptation to specific clinical contexts.

ReUnity represents a fundamentally different approach to trauma-informed technology: rather than attempting to "fix" fragmentation, it provides tools for maintaining awareness and continuity across discontinuous states. This approach respects survivor autonomy while offering meaningful support during vulnerable periods.

Future work will focus on clinical validation, multilingual support, and integration with existing healthcare systems while maintaining the privacy-preserving, survivor-centered design principles that define the framework.

A Extended Social and Contextual Statistics

This appendix provides comprehensive statistical data supporting the problem statement in Section 1.

A.1 Montana Domestic Violence Statistics

Montana women experience intimate partner violence at a lifetime prevalence rate of 56.7%, significantly higher than many national averages. The state documented 248 domestic violence fatalities from 2000 to 2021, with 73% of victims being female.

Table 4: Montana Domestic Violence Statistics (2000-2021)

Metric	**Value**
Total DV Fatalities	248
Female Victims	73%
Lifetime IPV Prevalence (Women)	56.7%
Counties Without Trauma Providers	61%
Average Rural Response Time	45+ minutes

A.2 Rural Healthcare Access Barriers

Rural communities face systematic barriers to domestic violence intervention:

- Geographic isolation requiring travel of 100+ miles for specialized services
- Provider shortages with 61% of Montana counties lacking trauma-informed psychiatric providers
- Economic barriers limiting access to private transportation and lodging
- Cultural factors emphasizing family privacy and community reputation

A.3 Institutional Failure Case Studies

A.3.1 Montana State University

Between 2018 and 2023, Montana State University received over $2.3 million in federal Violence Against Women Act and Victims of Crime Act funding while engaging in documented patterns of retaliation against sexual assault survivors. Specific violations included manipulation of investigation timelines, witness coaching, weaponization of No-Contact Orders, and accessibility violations preventing disabled survivors from participating in proceedings.

A.3.2 Darcy Buhmann Case

Darcy Buhmann was murdered by her ex-partner in rural Montana after seeking help from multiple institutional systems. The case revealed systematic failures including delayed law enforcement response, lack of trauma-informed providers within 150 miles, legal system delays, and economic barriers limiting relocation options.

B Mathematical Derivations

B.1 Shannon Entropy Properties

The Shannon entropy function $H(X) = -\sum p(x) \log_2 p(x)$ has the following properties relevant to emotional state analysis:

1. **Non-negativity:** $H(X) \geq 0$ for all distributions
2. **Maximum:** $H(X) \leq \log_2 n$ where n is the number of states
3. **Concavity:** $H(\lambda P + (1-\lambda)Q) \geq \lambda H(P) + (1-\lambda)H(Q)$

B.2 Jensen-Shannon Divergence Derivation

The JSD is derived from the Kullback-Leibler divergence:

$$D_{KL}(P||Q) = \sum_i P(i) \log_2 \frac{P(i)}{Q(i)} \tag{6}$$

$$M = \frac{1}{2}(P + Q) \tag{7}$$

$$JSD(P||Q) = \frac{1}{2} D_{KL}(P||M) + \frac{1}{2} D_{KL}(Q||M) \tag{8}$$

The JSD is symmetric ($JSD(P||Q) = JSD(Q||P)$) and bounded ($0 \leq JSD \leq 1$).

B.3 Lyapunov Exponent Calculation

For a discrete dynamical system $x_{n+1} = f(x_n)$, the Lyapunov exponent is:

$$\lambda = \lim_{N\to\infty} \frac{1}{N} \sum_{n=0}^{N-1} \log |f'(x_n)| \tag{9}$$

In practice, we approximate this using finite time series with appropriate windowing.

C Implementation Details

C.1 Repository Structure

```
ReUnity/
+-- src/reunity/
|   +-- core/
|   |   +-- entropy.py
|   |   +-- free_energy.py
|   +-- router/
|   |   +-- state_router.py
|   +-- protective/
|   |   +-- pattern_recognizer.py
|   |   +-- safety_assessment.py
```

```
|   +-- memory/
|   |   +-- continuity_store.py
|   |   +-- timeline_threading.py
|   +-- regime/
|   |   +-- regime_controller.py
|   +-- alter/
|   |   +-- alter_aware.py
|   +-- api/
|       +-- main.py
+-- tests/
+-- data/
+-- docs/
```

C.2 Reproduction Instructions

```
git clone https://github.com/ezernackchristopher97-cloud/ReUnity
cd ReUnity
make setup
make sim-download-data
make sim-real
```

C.3 Configuration Parameters

Table 5: Default Configuration Parameters

Parameter	Description	Default
entropy_window	Sliding window size	10
jsd_threshold	Maximum divergence for edges	0.5
mi_threshold	Minimum mutual information	0.1
lyapunov_window	Stability calculation window	20
crisis_threshold	Entropy threshold for crisis	4.0

D Additional Figures

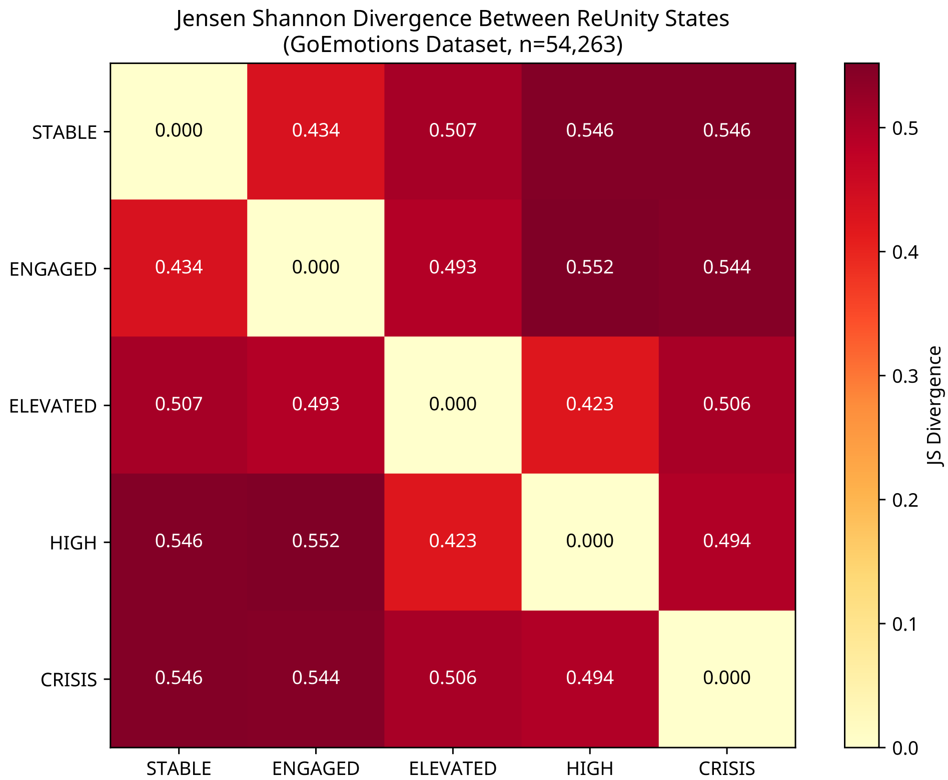

Figure 6: Jensen-Shannon divergence matrix between ReUnity emotional states.

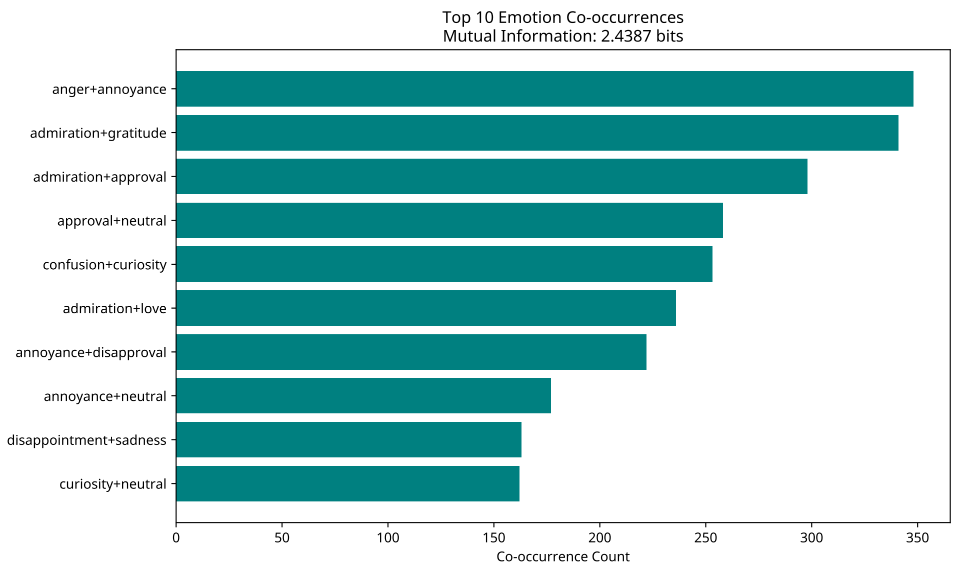

Figure 7: Top 10 emotion co-occurrences showing mutual information between pairs.

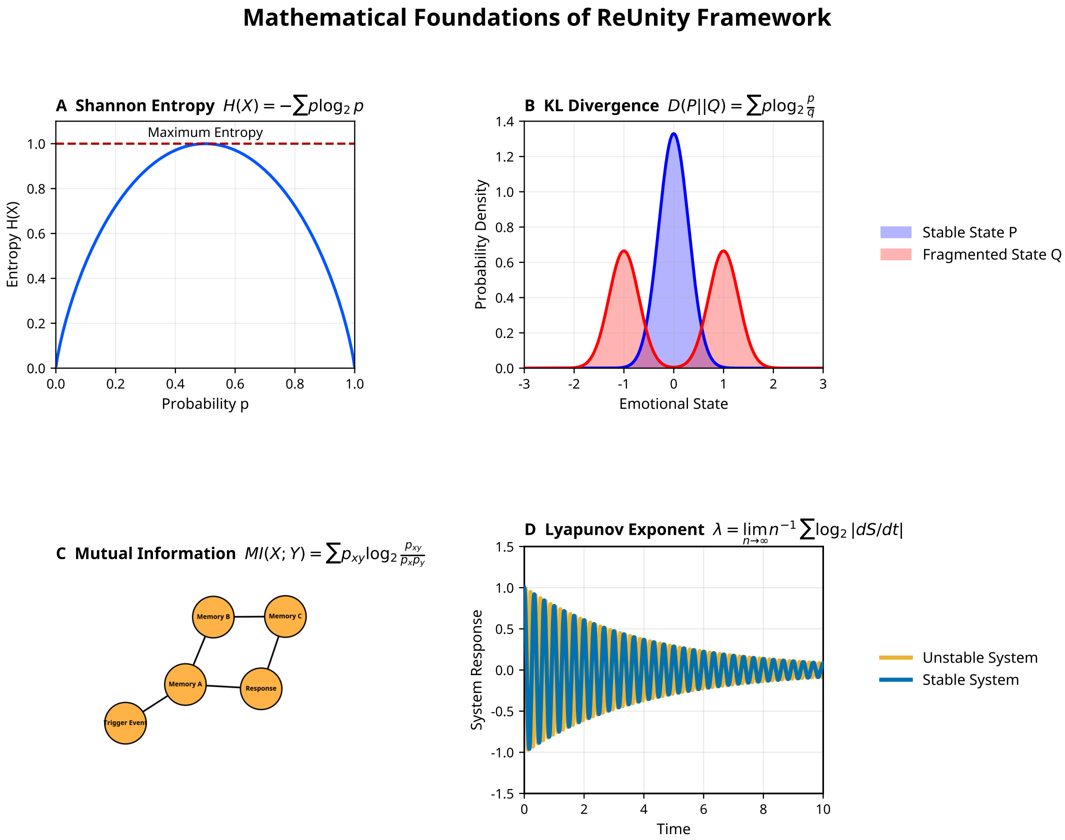

Figure 8: Mathematical foundations visualization showing entropy, divergence, and stability relationships.

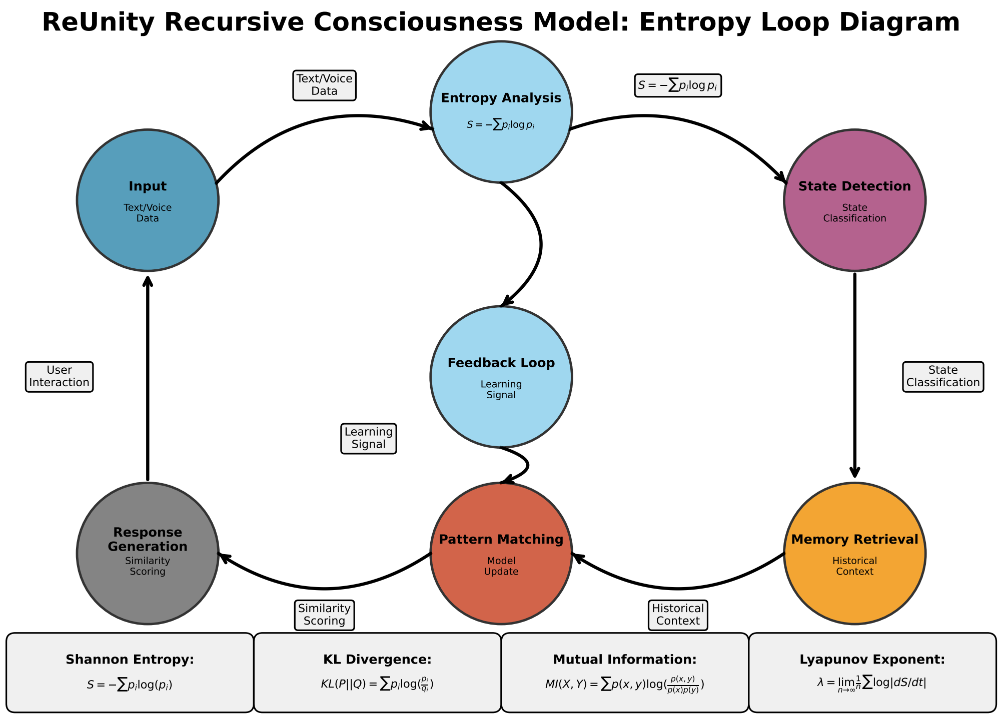

Figure 9: Recursive consciousness flow diagram showing information processing pathways.