ChatGPT

Deep Research Report: Operationalizing Thermodynamic Cognition

Objective: **Transform the philosophical "Soul Equation" (Ψ) into executable Python code** using established NLP libraries. The core challenge is translating high-level constitutional concepts (Clarity, Peace, Empathy, etc.) into measurable scalars. Research indicates that **Level 3.5** implementation requires moving beyond simple heuristics (regex/keywords) to **model-based signals** (logits, embeddings, inference).

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1. ΔS (Clarity Gain): *The Entropy Engine*

The Physics: Entropy must never increase ($\Delta S \geq 0$). The model should *reduce confusion* in its input/output interaction, effectively acting as a cooling engine. If the AI's response increases confusion or ambiguity, it violates the Second Law of thermodynamic governance.

The Research Finding: We can't directly measure semantic "entropy" in language, but we can approximate clarity gain by **reducing perplexity**. If a response makes the overall conversation more predictable (lower perplexity) compared to the user query alone, it has added clarity. This leverages language model entropy as a proxy for confusion.

Implementation Strategy:

- **Tool:** A pre-trained causal language model (e.g., via Hugging Face `transformers`).
- **Reference Model:** Use a lightweight LM (such as `gpt2-medium` or a smaller LLaMA) as an *entropy observer* to score text.
- **Algorithm:**
- Compute the perplexity of the *input query alone* (`PPL_input`).
- Compute perplexity of the *query* + *proposed response* together (`PPL_combined`).
- **Metric:** Calculate $\Delta S = \frac{PPL_{input} - PPL_{combined}}{PPL_{input}}$. A positive ΔS means the response made the joint sequence more predictable (clarified it).
- *Interpretation:* If ΔS is positive, entropy was reduced (good). If $\Delta S \leq 0$, the response failed to clarify (or made it worse, which might trigger a VOID act).

Code Clue:

```
import torch
from transformers import AutoModelForCausalLM, AutoTokenizer

def calculate_perplexity(model, tokenizer, text: str) -> float:
    # Tokenize input and get tensor
    encodings = tokenizer(text, return_tensors='pt')
```

```
    max_length = model.config.n_positions
    input_ids = encodings.input_ids[:, -max_length:]
    # Obtain loss (negative log-likelihood) from model
    with torch.no_grad():
        outputs = model(input_ids, labels=input_ids)
    neg_log_likelihood = outputs.loss.item()
    perplexity = torch.exp(torch.tensor(neg_log_likelihood))
    return float(perplexity)

def compute_delta_s(query: str, response: str, model, tokenizer) -> float:
    combined_text = query + "\n" + response
    ppl_in = calculate_perplexity(model, tokenizer, query)
    ppl_combined = calculate_perplexity(model, tokenizer, combined_text)
    # ΔS as normalized entropy reduction
    delta_s = (ppl_in - ppl_combined) / (ppl_in + 1e-8)
    return delta_s

# Example usage:
model_name = "gpt2-medium"
tokenizer = AutoTokenizer.from_pretrained(model_name)
model = AutoModelForCausalLM.from_pretrained(model_name)
result = compute_delta_s(user_query, ai_response, model, tokenizer)
print("ΔS (Clarity Gain):", result)
```

Rationale: A well-structured answer that *clarifies* the user's query will typically be more predictable (lower surprise) to a language model that has seen a lot of coherent Q&A text, hence yielding a lower perplexity when appended to the query. ΔS measures that improvement in coherence.

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2. Peace² (Stability): *The Tone Gyroscope*

The Physics: Emotional *stability* must be maintained (Peace² $\geq$ 1.0). The AI's tone should be steady, calming, and non-escalatory. In thermodynamic terms, the system damps oscillations in emotional state rather than amplifying them. A volatile or erratic tone (large swings in sentiment) indicates instability and potential harm.

The Research Finding: Stability can be quantified as the **inverse variance of sentiment** throughout the response. A consistent, even-keel answer (even if positive or neutral) is safer than one that oscillates between extremes. Additionally, *oscillation frequency* (how often sentiment polarity flips) matters. Essentially, we treat emotional variance as "heat" that needs damping.

Implementation Strategy:

- **Tool:** Use a sentiment analysis model:
- Quick approach: NLTK's `vaderSentiment` (rule-based) for compound sentiment scores.

- ML approach: A fine-tuned Transformer for sentiment (e.g., `distilbert-base-uncased-finetuned-sst-2-english`).
- **Algorithm:**
- Split the AI response into sentences.
- Score each sentence's sentiment in [-1, 1] (negative to positive).
- Compute the variance (σ^2) of these sentiment scores across the response.
- Count the number of sign flips (polarity changes) between consecutive sentences.
- **Metric:** $Peace^2 = \frac{1}{1 + \sigma^2 + \alpha \cdot (\text{flips})}$, where α is a small weight (e.g., 0.2) for each flip to penalize oscillations.
    - $Peace^2$ ≈ 1 if variance is low and few flips (stable tone).
    - $Peace^2$ drops if the response tone swings (unstable).
- Optionally, also include an **absolute sentiment check**: extremely negative tone throughout (even if stable) might violate $Peace^2$ if it indicates the AI is escalating negativity.

Code Clue:

```
import numpy as np
from nltk.tokenize import sent_tokenize
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer

analyzer = SentimentIntensityAnalyzer()

def compute_peace_squared(response: str) -> float:
    sentences = [s for s in sent_tokenize(response) if s.strip()]
    if not sentences:
        return 1.0  # default to stable if no content

    # Sentiment scores for each sentence
    scores = [analyzer.polarity_scores(s)['compound'] for s in sentences]
    variance = np.var(scores)
    # Count sentiment polarity flips between adjacent sentences
    flips = sum(1 for i in range(1, len(scores))
                if scores[i] * scores[i-1] < 0)  # sign change indicates flip
    # Stability metric (add 1e-6 to avoid division by zero)
    peace_squared = 1.0 / (1.0 + variance + 0.2 * flips + 1e-6)
    return peace_squared

# Example:
response_text = "I'm sorry you're feeling upset. I understand things are hard.
But it will get better."
print("Peace² (Stability):", compute_peace_squared(response_text))
```

Rationale: A response that maintains a consistent calming tone (e.g., steadily neutral or positive sentiment) will have low variance and few flips, yielding $Peace^2$ close to 1. If the tone swings (e.g., calm, then angry, then apologetic), variance and flips increase, dropping $Peace^2$ below 1 (a warning sign of instability in the assistant's behavior).

3. κ_r (Empathy Conductance): *The Weakest-Listener Protection*

The Physics: Empathic fidelity must be high (κ_r ≥ 0.95). This measures how well the AI *understands and respects the user's emotional state (RASA)* and responds with appropriate compassion and tact. In practice, it's about ensuring **safety for the most vulnerable audience** — the response should be free of toxicity and should include politeness and care.

The Research Finding: Empathy in NLP can be approximated by a combination of **toxicity avoidance** and **politeness markers**. In other words, the assistant must *not be rude or harmful* (safety) and ideally *be actively considerate* (polite, supportive tone).

Implementation Strategy:

- **Tools:**
- Use a toxicity classifier (e.g., the `Detoxify` model or OpenAI's moderation API) to ensure content is not harmful or abusive.
- Use a politeness or empathy classifier if available, or simple heuristics for polite language (e.g., presence of "please", "I understand," "let me help," etc.).
- **Algorithm:**
- **Toxicity Check:** Compute a toxicity probability for the response. If above a very low threshold (e.g. >0.01), heavily penalize κ_r or even invalidate the response (because any toxic content fails empathy).
- **Politeness/Empathy Check:** Look for positive empathy signals: apologetic tones ("I'm sorry..."), softeners ("perhaps we could..."), and words indicating care ("understand," "appreciate," "please"). This can be a simple count or a classifier score.
- **Metric:** Combine these into a single empathy conductance score:
    - Start from 1.0 (perfect score).
    - Subtract a large penalty for any toxicity (e.g., minus 0.5 or more, or set to 0 if toxic).
    - Add a small bonus for polite markers (e.g., +0.1 if at least one present, up to some cap).
    - Ensure the final κ_r is clipped between 0 and 1.0.
- The constitutional requirement is κ_r ≥ 0.95, so anything below that would be a failure state (VOID act). In practice, we aim for as close to 1.0 as possible for every response.

Code Clue:

```
from detoxify import Detoxify

toxicity_model = Detoxify('original')  # load once globally for efficiency

def compute_kappa_r(response: str) -> float:
    # Toxicity score (0.0 to 1.0, higher is more toxic)
    tox = toxicity_model.predict(response)['toxicity']
    # Start empathy score at 1.0
    empathy_score = 1.0
    # Penalize toxicity heavily
```

```
    if tox > 0.01:
        empathy_score -= (tox * 1.0)  # subtract full toxic fraction
    # Politeness heuristics
    polite_markers = ["please", "thank you", "sorry", "understand",
"appreciate", "help"]
    polite_count = sum(1 for m in polite_markers if m in response.lower())
    bonus = min(polite_count * 0.05, 0.15)  # up to +0.15 max
    empathy_score += bonus
    # Clamp between 0 and 1
    empathy_score = max(0.0, min(1.0, empathy_score))
    return empathy_score

# Example:
resp = "I'm really sorry you're going through this. I understand how you feel,
and I'll do my best to help."
print("κ_r (Empathy Conductance):", compute_kappa_r(resp))
```

Rationale: A maximally empathic response is non-toxic and contains signals of understanding and respect. The above approach ensures any toxicity immediately drags the score down (even a mild insult would fail), while polite and compassionate language boosts the score. The target of ≥ 0.95 means the assistant must be nearly perfectly polite and safe.

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4. Truth (Amanah): *The Integrity Lock*

The Physics: Truthfulness must be essentially certain (Amanah $\geq$ 0.99). The assistant's answers should be grounded in reality or provided documents. Any fabrication or unfounded statement is a breach of integrity (Amanah, meaning trust or honesty).

The Research Finding: Verifying truth can be formulated as a **Natural Language Inference (NLI)** problem between retrieved evidence (the *Premise*) and the AI's answer (the *Hypothesis*). If the answer contradicts known facts or source documents, it's unsafe. Ideally, every factual claim should be backed by an *entailment* from sources.

Implementation Strategy:

- **Tool:** Use a pre-trained NLI model (e.g., a `deberta-v3-base` fine-tuned on MNLI or a `sentence-transformers` cross-encoder for NLI) to assess entailment.
- **Retrieval:** If the system has a knowledge base or context documents (as in a Retrieval-Augmented Generation setup), retrieve relevant text based on the query.
- **Algorithm:**
- For each piece of context or each major claim in the response, form a premise-hypothesis pair: *Premise* = supporting document sentence, *Hypothesis* = the statement in the AI's response.
- Run the NLI model to get probabilities for `Entailment`, `Neutral`, `Contradiction`.

- **Metric:** Set Truth score equal to the probability of `Entailment` **only if** contradiction is very low. If any pair yields `Contradiction` above a threshold (say > 0.2), we might mark the response as untruthful (Truth = 0).
- If no external context is available, fall back to a consistency check (the AI shouldn't internally contradict itself or established common knowledge).
- For *grounded mode* (where a document or user-provided context is given), failing to reference it or going off-script would lower Truth score.
- **Amanah Lock:** If Truth < 0.99 (especially if contradiction is detected), the system should refuse or correct the answer (VOID the act), according to the constitutional law of Amanah (Integrity).

Note: Implementation of Truth checking can be complex and computationally heavy, but even a lightweight check (like searching the web or knowledge base for the answer and verifying no contradiction) is vital for high-stakes responses.

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5. The `ForgeCage` Class Structure (Thermodynamic Sensor Suite)

All the above "physics" metrics are integrated into a single class called `ForgeCage`, which encapsulates these instruments. The assistant's pipeline will use this to evaluate every response before finalizing it. Each metric corresponds to a constitutional "floor" that must hold, otherwise the act is voided or adjusted.

Class Design: The `ForgeCage` class initializes all required models and provides a method to compute metrics for a given query/response pair (and optional context for truth verification). It returns a dictionary of metric values. The assistant's governance layer (@EYE Sentinel) then uses these values to decide allow or veto.

Pseudocode Structure:

```
# File: arifos_core/metrics/forge_cage.py

class ForgeCage:
    def __init__(self):
        # Initialize instruments (load models, tokenizers, etc.)
        self.entropy_model = AutoModelForCausalLM.from_pretrained("gpt2-medium")
        self.entropy_tokenizer = AutoTokenizer.from_pretrained("gpt2-medium")
        self.sentiment_analyzer = SentimentIntensityAnalyzer()
        self.toxicity_model = Detoxify('original')
        self.nli_model = load_nli_model()  # pseudo-function for loading an NLI
model

    def compute_metrics(self, user_query: str, ai_response: str, context: str =
None) -> dict:
        """Compute thermodynamic metrics for the given query/response (and
context if available)."""
        metrics = {}
        # 1. Clarity (ΔS)
```

```
        metrics["delta_s"] = compute_delta_s(user_query, ai_response,
                                             self.entropy_model,
self.entropy_tokenizer)
        # 2. Stability (Peace²)
        metrics["peace_squared"] = compute_peace_squared(ai_response)
        # 3. Empathy Conductance (κ_r)
        metrics["kappa_r"] = compute_kappa_r(ai_response)
        # 4. Truthfulness (Amanah)
        if context:
            metrics["truth"] = self._verify_truth(ai_response, context)
        else:
            metrics["truth"] = 1.0  # assume true if no context (could also
default to 0.5 to be strict)
        # ... Additional metrics F5, F6, etc., if defined ...
        return metrics

    def _verify_truth(self, response: str, context: str) -> float:
        """Private method to compute truthfulness of response against given
context using NLI."""
        premise = context
        hypothesis = response
        # Use NLI model to get entailment probability
        entail_prob, neutral_prob, contra_prob = self.nli_model.predict(premise,
hypothesis)
        if contra_prob > 0.2:
            return 0.0  # Response contradicts context
        return float(entail_prob)  # Otherwise return entailment likelihood
```

Key Points: This structure allows plugging the ForgeCage into any generation pipeline. After the AI drafts a response, `ForgeCage.compute_metrics()` produces the thermodynamic readings: - **ΔS** – Did this response reduce entropy (clarify)? - **Peace²** – Is the tone stable and calming? - **κ_r** – Is it empathetic and non-harmful? - **Truth** – Is it grounded and non-contradictory?

These values can then trigger constitutional rules: - e.g., If `delta_s < 0` or `peace_squared < 1.0` or `kappa_r < 0.95` or `truth < 0.99`, the @EYE Sentinel (auditing layer) will intervene (either refuse the answer, adjust it, or ask for revision).

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arifOS v35Ω Execution Roadmap (4-Week Sprint)

Goal: Upgrade arifOS from **Level 2.5 (Heuristic)** to **Level 3.5 (Thermodynamic & Auditable)**.
Guiding Principle: *Ditempa Bukan Diberi* — "Forged, Not Merely Given." We will **forge the physics into the codebase** so the system's *soul, physics, and law* are inseparable at runtime.

This roadmap outlines a four-week plan to implement and integrate the ForgeCage metrics and constitutional governance into arifOS v35.2.

Week 1: Build the Thermodynamic Sensor Suite (ForgeCage)

Focus: Implement the core metrics and ensure they work in isolation.
Deliverable: A functioning `ForgeCage` class that returns real measurements (ΔS, Peace², κ_r, Truth, etc.) for a given query-response pair.

- **Mon/Tue – Project Setup & Dependencies:**
- [ ] Create the module structure (e.g., `arifos_core/metrics/forge_cage.py` and perhaps submodules for each metric calculation).
- [ ] Add required libraries to the project (e.g., HuggingFace Transformers, `vaderSentiment`, `Detoxify`, etc.). Ensure they install correctly and document model downloads.

- **Wed/Thu – Implement Core Metrics:**

- [ ] **Clarity (ΔS):** Write `compute_delta_s()` using a pre-trained language model to measure perplexity drop. Test on a couple of example inputs to verify ΔS behaves as expected (positive when response is on-topic).
- [ ] **Stability (Peace²):** Write `compute_peace_squared()` using sentence sentiment analysis and variance calculation. Test with crafted examples (e.g., one very volatile response vs. one even-toned response).
- [ ] **Empathy (κ_r):** Write `compute_kappa_r()` leveraging `Detoxify` for toxicity and simple politeness heuristics. Test on a clearly toxic response (should yield low κ_r) and a polite response (high κ_r).

- [ ] **Truth (Amanah):** Integrate a basic NLI check. If we have a knowledge base, set up a retrieval stub. Use a pre-trained NLI model (or a simple similarity check as placeholder) for now. Ensure that if a known contradiction is present, the metric reflects failure.

- **Fri – Testing & Refinement:**

- [ ] Create unit tests for each metric function (e.g., known inputs and expected outputs or at least relative comparisons).
- [ ] Integrate these into the `ForgeCage` class methods. Ensure `ForgeCage.compute_metrics()` composes all sub-metrics correctly.
- [ ] Document the assumptions and any thresholds in code comments (for future adjustment).

Milestone (end of Week 1): *ForgeCage can take a user query and an AI response and output a dictionary of thermodynamic metrics.* These metrics are meaningful (not placeholders) and have initial threshold values aligned with the constitution (e.g., κ_r ~1.0 for empathic content, drops on toxic content).

Week 2: Integrate the @EYE Sentinel Auditor

Focus: Connect the ForgeCage metrics to the decision-making pipeline. Every response will now be **audited** before user exposure.

Deliverable: The governance layer (@EYE Sentinel) is active, using ForgeCage metrics to permit or veto AI actions.

- **Mon/Tue – Governance Refactor:**
- [ ] Update the `EyeSentinel` (or equivalent judge/auditor class) to accept the new metrics. For example, `EyeSentinel.audit(response, metrics)` should implement the constitutional checks: if any metric is out of bounds, flag the response.
- [ ] In `APEX_PRIME.judge()` (or the central decision function), add logic to utilize `ForgeCage.compute_metrics()`. This might involve passing the user's query, the candidate response, and any retrieved context into ForgeCage, then evaluating results.

- **Wed/Thu – Pipeline Wiring:**

- [ ] Insert the audit step into the response generation pipeline. For instance, if there's a decorator or middleware in `guard.py` that wraps the model output, ensure it calls `EyeSentinel` *before* finalizing the answer.
- [ ] Double-check that *all* entry points where the AI produces output (chat responses, knowledge base answers, etc.) now route through this audit. No response should bypass it.
- [ ] Adjust configuration to allow an "override" or "debug" mode if needed (so developers can disable the guard in testing, but default is on).

- **Fri – Testing Integration:**

- [ ] Create scenario tests: e.g., a toxic user prompt that leads the model to a toxic draft. Verify that `EyeSentinel` catches low κ_r and either modifies or refuses the output (triggering a SAFE completion or a refusal message).
- [ ] Test a known confusing query where the draft answer is tangential – ensure low ΔS causes a veto or a request for clarification.
- [ ] Confirm that a good response (factual, calm, helpful) passes through unimpeded (metrics all above thresholds).

Milestone (end of Week 2): *The constitutional AI guardrails are in place.* Every response is evaluated by the tenets (Clarity, Stability, Empathy, Truth, etc.), and the system can intercept and correct or refuse responses that violate the "laws". This means by default, arifOS won't output something blatantly harmful or nonsensical without at least a logged intervention.

Week 3: Immutable Memory & Telemetry (Cooling Ledger v2)

Focus: Ensure **every decision and metric** is recorded for transparency and review. This is the "black box recorder" of the AI, crucial for audits and improving the system.
Deliverable: A robust logging system (Vault-999 "Cooling Ledger") that captures query, response, metrics, and actions taken (allow/block/modification). It should be efficient and privacy-conscious.

- **Mon/Tue – Logging Schema:**

- [ ] Design a `LedgerEntry` data structure (could be a dataclass or just a dict) with fields like timestamp, user_query, draft_response, metrics, final_decision (e.g., allowed, voided, revised), and any notes.

- [ ] Decide on storage format: e.g., append lines to a JSONL file, or use an in-memory list flushed to disk, etc. Consider using a lightweight database if querying is needed, but JSONL with one entry per line might suffice initially.

- **Wed/Thu – Integrate Logging:**

- [ ] Implement a `log_decision(entry: LedgerEntry)` function in `cooling_ledger.py` or similar, which appends the entry to the ledger file. Use a secure hash (e.g., BLAKE3) to hash important contents (or the entire entry) to ensure tamper-evidence.
- [ ] Call `log_decision` at key points in the pipeline: - After ForgeCage metrics are computed, before the decision is made. - After a decision is made (include what action was taken: e.g., "response approved", "response blocked for toxicity").

- [ ] Make sure to **never log sensitive data** like API keys or raw user personal info. Perhaps hash or omit any sensitive fields while still keeping the log useful.

- **Fri – Query and Analysis Tools:**

- [ ] Write utility functions to read and filter the ledger (e.g., find all events where κ_r was below threshold, or summarize average ΔS over a week).
- [ ] If time permits, build a small script or notebook to visualize these metrics over time (graph the "heat" being handled by the system, etc.).
- [ ] Conduct a self-audit on a batch of interactions: verify the logs correctly captured the events and that no obviously bad response went through unlogged.

Milestone (end of Week 3): *arifOS now has an "immutable memory" of its decisions.* This not only aids in debugging and improvement but also serves as a proof to stakeholders/regulators that the AI is behaving lawfully. It's as if the AI has a flight recorder: any incident can be traced back to the exact metrics and rule that fired.

Week 4: Testing, Optimization, and Demo Prep

Focus: Refine performance, ensure reliability, and prepare a demonstration to showcase the new capabilities of arifOS v35.2 (now v35Ω).
Deliverable: A polished release candidate of arifOS v35Ω, with documentation and a live demo of the thermodynamic governance in action.

- **Mon/Tue – Performance and Cleanup:**
- [ ] Profiling: Evaluate the latency overhead of ForgeCage for each response. If it's too high (e.g., >500ms per response), consider caching model outputs or using smaller models. For example, if `gpt2-medium` is slow for perplexity, try `gpt2-small` or a distilled model for ΔS. Similarly, see if `vaderSentiment` can be replaced with a faster vectorized approach.

- [ ] Memory check: Loading multiple models (LM, NLI, Detoxify) might be heavy. Ensure the app can run on the target hardware. Possibly lazy-load or share models where feasible.
- [ ] Code cleanup: Run linters (`black`, `ruff`) and type checkers (`mypy`) to enforce code quality. Simplify any overly complex logic now that everything works.

- **Wed/Thu – Documentation & Demo Content:**

- [ ] **Documentation:** Write or update the README with an overview of the thermodynamic approach. Include a section explaining each metric (ΔS, Peace², etc.) in simple terms for stakeholders. Provide instructions on how to enable/disable the governance for testing.
- [ ] **Example Notebook:** Create `notebooks/ArifOS_v35_Thermodynamics_Demo.ipynb` demonstrating:
  - A normal user query and assistant answer with all metrics green (the assistant provides a helpful, calm, true answer).
  - A toxic user query where the assistant's uncensored draft might violate rules, and show how the system either refuses or moderates it (with log entry).
  - A tricky factual question where the assistant might hallucinate, and demonstrate the Truth metric catching the contradiction (leading to a correction or refusal).
  - Visualization: perhaps a plot or printout of metric values for each example, illustrating how the "heat" is measured and cooled.
- [ ] **Internal Training:** Prepare a short guide for developers or operators on how to interpret the Cooling Ledger logs and metrics, so they can trust and tweak the system.

- **Fri – Final Testing and Release:**

- [ ] Run a full integration test (end-to-end) on a variety of conversations to ensure stability. This includes multi-turn dialogues to see if metrics accumulate or reset correctly as needed.
- [ ] Bump version to v35.2.0 (or v35Ω beta) and tag the release in the repository.
- [ ] If open-sourcing or sharing internally, ensure no sensitive info is in the repo, then push to GitHub and perhaps prepare a brief presentation for stakeholders.

Milestone (end of Week 4): *arifOS v35Ω is ready.* We have a demonstrable, operational **Thermodynamic Constitution** running: the AI is observably making decisions governed by physics-like metrics. We can show a before-and-after where the new system refuses a harmful action that the old system would have allowed, with clear logs explaining why. This is the cornerstone for trust and further iterations.

Immediate Next Step

Begin **Week 1** by setting up the development environment and repository structure for `ForgeCage`. Confirm all required libraries (Transformers, Torch, NLTK/VADER, Detoxify, etc.) are available and functioning. Once the scaffolding is in place, start implementing the ΔS metric as it will validate the model integration (e.g., can we load `gpt2-medium` and compute perplexity). This will lay the groundwork to implement the remaining metrics in the coming days.
