```
# Theoretical Analysis of Private Cloud Compute Security Boundaries
## 1. Key Architectural Components
Let's define the system formally:
- D: User Device (trusted endpoint)
- N: PCC Node (compute unit)
- M: Language Model
- SE: Secure Enclave
- K: Cryptographic Keys
- R: Request Data
- T: Transparency Log
## 2. Critical Security Claims Analysis
### 2.1 Stateless Computation Claim
\forall r \in R, \exists t : t_1 < t < t_2 where:
State(N, t_1) = State(N, t_2)
This implies complete state reset between computations. However, side-channel
analysis suggests:
∃δ where:
Information(State(N, t_2)) - Information(State(N, t_1)) \geq \delta
Due to physical memory remanence and deterministic model behavior.
### 2.2 Non-Targetability Analysis
Let's define the targeting function:
T(u, n) \rightarrow \{0,1\} where:
u = user identifier
n = node identifier
```

Apple claims: $\forall u_1, u_2, n: P(T(u_1, n)) = P(T(u_2, n))$

```
However, the threat model should consider:
∃f where:
f(behavioral_pattern) → user_identity
### 2.3. Critical Boundaries
The system presents three key theoretical boundaries:
1. Physical Security Boundary
Trust(N) = min(Trust(SE), Trust(Hardware))
2. Information Flow Boundary
\forall r \in R: Flow(r) \subseteq \{D \rightarrow N \rightarrow D\}
3. Temporal Boundary
\foralldata \in N, \existst: lifetime(data) \leq t
## 3. Theoretical Attack Surfaces
### 3.1 Model-Level Attack Surface
Consider the language model M as a function:
M: Input × State → Output × State'
Key observation: The model must maintain coherent state during inference, creating a
theoretical window where:
\exists s \in State where:
Extract(s) → PreviousInputData
### 3.2 Timing Channel Analysis
```

```
For any two requests R_1, R_2:
|ProcessingTime(R_1) - ProcessingTime(R_2)| \rightarrow InformationLeakage
This suggests a potential covert channel even with perfect cryptographic boundaries.
## 4. Novel Security Considerations
### 4.1 Neural State Persistence
Given the requirement for stateless computation, consider:
\forall n \in Neurons:
State(n, t_1) \perp State(n, t_2)
However, neural network optimization requires:
∃w ∈ Weights:
w(t_1) = w(t_2)
This creates a fundamental tension between model performance and perfect privacy
guarantees.
### 4.2 Theoretical Mitigation Boundaries
The system must satisfy:
∀attack ∈ AttackSpace:
P(Success(attack)) \le \varepsilon
Where \varepsilon represents acceptable security risk.
## 5. Research Implications
1. The transparency log T provides:
Verify(N) \rightarrow \{true, false\}
```

• • •

```
But cannot prove:

∀t: State(N, t) ∈ ValidStates

2. Hardware security boundary requires:

Trust(System) ≤ min(Trust(Components))
```

This suggests potential research directions in:

- 1. Formal verification of neural state reset
- 2. Side-channel resistant model architectures
- 3. Provable bounds on information leakage