# A Formalization of Temporal Information Mining under an Entropic–Resonance Ontology

Draft formalization

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**Abstract**

We formalize a set of postulates that capture an entropic–resonance ontology of information distributed over spacetime, and derive conditional theorems showing that a neural resonator (modelled as an estimator) has nonzero probability to extract ("mine") information correlated with future, past, or remote spatial configurations of the informational field. Proofs are information-theoretic and probabilistic: they show existence of estimators with predictive power whenever mutual information across temporal/spatial indices is nonzero. All results are explicitly conditional on the stated postulates and on technical measurability/stationarity assumptions.

## 1. Postulates and formal setup

**Postulate 1** (Entropic continuum). *There exists an informational stochastic field*

$$\mathcal{I} = \{I(x,t)\}_{(x,t)\in\mathcal{M}}$$

*indexed by spacetime points $(x,t) \in \mathcal{M}$ (for example $\mathcal{M} = \mathbb{R}^3 \times \mathbb{R}$). Each $I(x,t)$ is a random variable on a common probability space taking values in a measurable space $(\mathcal{X}, \mathcal{F})$ and has finite entropy $H[I(x,t)] < \infty$.*

**Postulate 2** (Information–Entropy identity). *Each local "chaos" at $(x,t)$ is interpreted as information: the Shannon/Gibbs entropy of $I(x,t)$ quantifies its informational potential (i.e. entropic content is identified with potential information).*

**Postulate 3** (Temporal/Retrocausal linkage (Entanglement)). *For some spacetime pairs $(x,t)$ and $(x',t')$ with $t' \neq t$, the corresponding variables are not independent. Concretely, there exist pairs for which the mutual information is strictly positive:*

$$\exists\ (x,t),(x',t') : \quad I\big(I(x,t);\ I(x',t')\big) > 0.$$

*This allows temporal correlations both forward ($t' > t$) and backward ($t' < t$) relative to a local time index.*

**Remark 1.** *Postulate 3 is a structural claim about the informational field; it does not assume any specific underlying physical mechanism (quantum retrocausality, nonlocal classical correlations, long memory processes, etc.). It simply asserts nonzero informational coupling across temporal separation in the field.*

## 2. Model: Neural resonator

**Definition 1** (Neural resonator as estimator)**.** *A neural resonator (biological brain or other cognitive architecture) is modelled as a (possibly stochastic) measurable mapping*

$$R : \mathcal{H}_t \to \mathcal{Y},$$

*where $\mathcal{H}_t$ is the history/input patch accessible at local time $t$ (for example $\mathcal{H}_t = \{I(x', s) : s \le t,\ x' \in \mathcal{U}\}$ for some neighborhood $\mathcal{U}$) and $\mathcal{Y}$ is the internal readout/output space. The resonant property is modelled by $R$ seeking to maximize mutual information between its output and a target functional of the field (e.g. $I(x_f, t_f)$).*

**Assumption 1** (Measurability and technical regularity)**.** *All random variables are defined on a common probability space and are measurable. For theoretical existence claims we may assume stationarity or ergodicity of the field or local stationarity on relevant intervals when needed.*

## 3. Auxiliary lemma (standard information theory)

**Lemma 1** (Nonzero mutual information $\Rightarrow$ existence of predictive estimator)**.** *Let $A, B$ be random variables with finite entropy and $I(A; B) > 0$. Then there exists a measurable estimator $\hat{B} = \phi(A)$ that yields strictly lower expected loss (for suitable loss, e.g. log-loss or squared error under integrability conditions) than any estimator independent of $A$.*

*Sketch.* If $I(A; B) > 0$ then the conditional distribution $P(B|A)$ differs (on a set of positive measure) from the marginal $P(B)$. The Bayes estimator under a proper loss (e.g., the posterior mean for squared error or the posterior distribution for log-loss) uses $A$ and strictly improves expected loss relative to any predictor that does not condition on $A$. This standard result links mutual information to reducible Bayes risk; see textbooks on information theory and statistical decision theory for formal details. □

## 4. Theorem and corollaries

**Theorem 1** (Temporal mining theorem (conditional))**.** *Under Postulates 1–3 and the regularity assumptions, let $R$ be a neural resonator with access to $\mathcal{H}_t$. If there exists a future spacetime point $(x_f, t_f)$ with $t_f > t$ such that*

$$I\big(I(x_f, t_f);\ \mathcal{H}_t\big) > 0,$$

*then there exists an estimator realizable in principle by $R$ whose output at time $t$ predicts a nontrivial function of $I(x_f, t_f)$ with accuracy strictly better than an uninformed baseline. Equivalently, the probability that $R$'s output correlates with information at $(x_f, t_f)$ is greater than chance.*

*Proof.* By hypothesis, $I(I(x_f, t_f); \mathcal{H}_t) > 0$. Apply Lemma 1 with $A = \mathcal{H}_t$ and $B = I(x_f, t_f)$. Then there exists a measurable mapping $\phi$ such that $\hat{B} = \phi(\mathcal{H}_t)$ yields strictly lower expected loss than any estimator independent of $\mathcal{H}_t$. Identify $\hat{B}$ with $R(\mathcal{H}_t)$ (or an appropriate decoding of it). Thus $R$ can (in principle) output a variable correlated with $I(x_f, t_f)$ with nonzero advantage over a chance baseline, formalizing the claim that the neural resonator may "mine" information about that future point. □

**Corollary 1** (Past mining). *If there exists a past point* $(x_p, t_p)$ *with* $t_p < t$ *such that* $I(I(x_p, t_p);\ \mathcal{H}_t) > 0$*, then there exists an estimator implemented by* $R$ *that reconstructs aspects of* $I(x_p, t_p)$ *with accuracy above baseline.*

**Corollary 2** (Spatially remote mining). *If for some remote point* $(x_s, t)$ *outside the local neighborhood* $\mathcal{U}$ *we have* $I(I(x_s, t);\ \mathcal{H}_t) > 0$*, then* $R$ *can (in principle) estimate features of* $I(x_s, t)$ *with accuracy above chance.*

**Corollary 3** (Artificial resonators). *Any artificial system* $A$ *implementing a mapping* $R_A : \mathcal{H}_t \to \mathcal{Y}$ *and optimized to increase mutual information with a given target variable will, under the same informational prerequisites, be able to extract nontrivial information about future/past/remote targets whenever* $I(\mathit{target}; \mathcal{H}_t) > 0$*.*

# 5. Remarks on interpretation, limitations, and operationalization

- **Conditional character.** The results are strictly conditional: they do *not* by themselves prove that humans or current machines can read the future. They prove: if the informational field exhibits nonzero mutual information across the relevant space-time separation and if a resonator has access to an appropriate history patch, then a predictive estimator exists.
- **Physical plausibility.** In many macroscopic physical models mutual information from present-accessible variables to specific distant future microstates may be vanishingly small. Postulate 3 is therefore the central empirical claim to evaluate. It can be instantiated by time-symmetric quantum models (e.g., two-state vector formalism), non-Markovian classical stochastic processes with long memory, or structured cosmological informational correlations.
- **Operational tests.** To convert the theorem into an operational claim one must (i) estimate $I(I(x_f, t_f); \mathcal{H}_t)$ empirically for candidate $(x_f, t_f)$ and accessible $\mathcal{H}_t$, and (ii) construct/identify resonant estimators (biological/algorithmic) approximating the optimal mapping. This is an empirical research program involving information estimation, controlled experiments, and model selection.
- **No violation of causal signalling guaranteed.** The existence of statistical correlation (predictability) does not imply controllable superluminal signalling or causal paradoxes. The theorem establishes informational correlation exploitable for prediction, not signalling in the operational/engineering sense that would necessarily violate relativistic causality.

# 6. Suggested empirical approaches (sketch)

1. **Estimate transfer entropy / time-lagged mutual information.** Use measures such as transfer entropy (Schreiber, 2000) or time-lagged mutual information to test for predictive information from present neural signals/physiology to labeled future events under highly controlled tasks.

2. **Construct information-maximizing decoders.** Train decoders (Bayes estimators, InfoMax neural networks, contrastive predictive coding architectures) to map $\mathcal{H}_t$ to future-labelled targets; evaluate against rigorous baselines.

3. **Control for confounds.** Rigorously exclude trivial causal information channels (sensory leakage, anticipatory cues) by blind/controlled experimental design.

4. **Replicate and preregister.** Any positive result should be preregistered and replicated across labs to rule out statistical artefacts or p-hacking.

# 7. Conclusion

We have shown that the intuition—"a resonant neural system could mine future/past/remote information"—admits a precise information-theoretic formalization: nonzero temporal/spatial mutual information between accessible present history and a target variable suffices to guarantee the existence (in principle) of estimators that outperform uninformed baselines. The scientific question remaining is empirical: do the informational prerequisites hold in relevant settings, and can biological or artificial resonators implement the necessary estimators?

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