Event-Based Time: A Quantitative Framework for Measuring Temporal Flow through Event Density and Information Change

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Abstract

The conventional definition of time as an independent dimension assumes that temporal flow exists objectively, regardless of system activity. However, in many dynamic systems—from physical processes to information networks—time manifests only through observable change. This paper proposes a framework that defines **time as event density**: a measure of how many distinct state transitions occur within a given observation window. By modeling event occurrence as a stochastic process and mapping its entropy evolution, we treat time not as an external parameter but as an emergent property of information change. This perspective links the phenomenological experience of time to measurable computational and physical processes. The proposed model offers a unifying view of time across physical, informational, and cognitive domains, suggesting that temporal flow is fundamentally a measure of change propagation and entropy growth rather than an independent backdrop.

Keywords: time as change; event density; information theory; entropy; complex systems; emergent time; stochastic processes

1 Introduction

The concept of time has traditionally been regarded as a universal and continuous dimension that orders events. From Newtonian mechanics to Einstein's relativity, time has functioned as a coordinate—either absolute or relative—upon which dynamics are plotted. However, in computational and information-driven systems, time is not always measured by clocks but by *events*: discrete occurrences that signal state transitions or data updates.

In this work, we explore a redefinition: **time as the measure of change itself**. Specifically, we define "temporal flow" as proportional to the number and distribution of state transitions within a given observation period. Instead of asking how much time passes between events, we ask how much change occurs within what we call "a unit of time."

This reframing aligns with the intuition that when no change occurs—no events happen, no state updates are registered—**time effectively stands still** from the system's perspective. The paper develops this intuition into a formal model connecting **event density**, **information entropy**, and **perceived temporal progression**.

2 Related Work

Several intellectual traditions have approached time as emergent from change.

In **philosophy**, Aristotle defined time as "the measure of change with respect to before and after." Bergson later emphasized the qualitative flow of change—"duration"—as a fundamental aspect of experience.

In **physics**, Rovelli's thermal time hypothesis and Barbour's timeless physics suggest that time emerges from relational configurations of events rather than existing absolutely.

In **information theory**, Shannon's entropy measures the uncertainty or information content of a state distribution. As systems evolve, their entropy often changes, providing a measurable indicator of informational time.

In **complex systems and computation**, event-driven architectures, asynchronous systems, and distributed ledgers measure progress by *event counts*, not clock ticks.

Building on these perspectives, this paper unifies them under a single operational idea: **time equals event density**—the rate of distinguishable changes relative to system state capacity.

3 Conceptual Framework

Let a system S be defined by a set of states $\{s_1, s_2, \ldots, s_n\}$. Events are transitions $e_i : s_i \to s_j$ that change the system's configuration.

We define:

$$E(t) = \text{number of events observed in window } t \tag{1}$$

and

$$\rho = \frac{E(t)}{t} \tag{2}$$

as the **event density** (events per observation window).

Inverting this relation gives the key conceptual shift:

$$t' = f(E) = k \cdot E \tag{3}$$

where t' is *experienced time* and k is a proportional constant linking the subjective passage of time to event count.

Thus, time is measured by change, not change by time. If no events occur ($E = 0$), then $t' = 0$: the system experiences no time.

4 Mathematical Model

4.1 Event Process as a Poisson Distribution

Let event occurrences follow a Poisson process with rate λ:

$$P(E(t) = k) = \frac{(\lambda t)^k e^{-\lambda t}}{k!} \tag{4}$$

Here λ represents the **average rate of change** or **temporal intensity**. If we redefine time as proportional to events, we invert the dependency:

$$t = \frac{E}{\lambda} \tag{5}$$

That is, the observed passage of time depends on how many events actually occurred.

This extends naturally to non-homogeneous systems where λ varies, allowing "time dilation" in complex systems—slower evolution where fewer events occur.

4.2 Information Entropy as Temporal Progress

For systems where each event changes information entropy H:

$$\Delta H = H(t + \delta) - H(t) \tag{6}$$

Then total experienced time can be expressed as:

$$T = \int \frac{dH}{\lambda(H)} \tag{7}$$

suggesting that **entropy growth defines the arrow of time**. When entropy ceases to change, time halts in a meaningful sense.

5 Simulation Concept

Consider a sensor network where events are data packets received.

- When the environment is active, packet arrivals (events) are frequent; event density ρ is high, perceived time flows quickly.
- When the system is idle (no packets), event density approaches zero; perceived time slows or halts.

The system's internal clock can thus be replaced by a self-measured temporal flow based on event counts. This approach can be implemented in AI agents, distributed ledgers, or self-organizing systems where conventional synchronization is impractical.

6 Discussion

6.1 Relation to Physical Time

This model does not deny physical time; it reinterprets it as emergent from interactions. In relativity, time dilates with energy and gravity; here, it dilates with event activity. Both describe how context determines the rate of experienced change.

6.2 Implications for Complex Systems

For complex adaptive systems—ecosystems, markets, or neural networks—event density varies dynamically. Periods of rapid change correspond to "fast time," while equilibria correspond to "slow time." This aligns with phenomena like market volatility, neural bursts, or social media activity.

6.3 Computational and Philosophical Implications

In computation, this model enables time-free simulation frameworks where causality replaces clock-based updates. In philosophy, it bridges physicalism and phenomenology: subjective time arises from perceived change, not from an external clock. In cosmology, it resonates with timeless formulations of quantum gravity, suggesting that before the first event, time had no meaning.

7 Conclusion

We have proposed a model of time defined not by an external parameter but by **the density of events and information change**. This reframing makes time an emergent property of system dynamics, measurable through event occurrence and entropy evolution. The approach unifies perspectives from information theory, physics, and complex systems, providing a quantitative foundation for understanding time as change itself.

Future work may formalize this through simulations linking event-based time to computational entropy production in machine learning or distributed systems.

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