Interdisciplinary Description of Complex Systems 24(2), 115-127, 2026

LUCK AS AN INFORMATIONAL OBSERVABLE FOR ANOMALY DETECTION IN SYSTEMS WITH MEMORY

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DOI: 10.7906/indecs.24.2.3
Regular article

Received: 13 December 2025.
Accepted: 3 February 2026.

ABSTRACT

The detection of anomalous events in noisy systems remains a fundamental challenge across physics, information theory, and complex systems. Conventional approaches typically rely on local statistical deviations, which often fail in non-stationary environments or in processes with long-term memory. In this work, we introduce luck as an informational observable that explicitly incorporates historical context into anomaly detection. Starting from an original convolution-based formulation involving the Dirac delta, luck is defined as the ratio between the local probability of an event and the cumulative probability accumulated by the system up to that point.

Unlike probability, luck is not bounded by unity and is undefined in the absence of history, reflecting the principle that anomalies require memory. By normalizing luck, we obtain a distribution that characterizes how unexpected information is allocated across events. The associated entropy of luck provides a global measure of the informational structure of a process, distinguishing between regular, quasi-deterministic dynamics and intermittent regimes dominated by rare, history-breaking events.

Through numerical experiments with strong noise and synthetic examples inspired by real-world systems, we demonstrate that luck-based analysis robustly suppresses background fluctuations while selectively amplifying genuine anomalies. Comparisons with classical local detectors show that the proposed framework operates without arbitrary thresholds and remains effective in highly noisy and non-stationary conditions. These results establish luck as a principled, computationally efficient, and broadly applicable informational observable – distinct from probability – that quantifies historical mismatch rather than frequency, making it suitable for anomaly detection in systems with memory.

KEY WORDS

information theory, anomaly detection, entropy, cumulative probability, systems with memory

CLASSIFICATION

JEL: C46

PACS: 05.40.-a, 89.70.Cf

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INTRODUCTION

The detection of anomalous events is a recurrent problem across physics, information theory, and complex systems. In many real-world applications – ranging from noisy physical signals to financial, institutional, and social processes – events of interest are not defined solely by their instantaneous probability, but by how they relate to the accumulated history of the system. Classical approaches to anomaly detection typically rely on local statistics, threshold rules, or short-time deviations, which are effective in stationary and low-noise environments but often fail in systems with long memory, strong correlations, or non-stationary dynamics [1-4].

From an informational standpoint, probability alone does not encode historical context. Two events with identical probability may carry very different informational significance depending on when they occur and on what the system has previously experienced. This limitation is well recognized in information theory and statistical inference, where information is understood as a relational quantity rather than an absolute one [1-6]. In processes characterized by heavy-tailed statistics or long-range correlations, rare events may be frequent enough to lose their discriminative power, while genuinely significant events are those that break accumulated expectations rather than merely local averages [7-11].

Several theoretical frameworks address rare or extreme events, including large deviation theory and extreme value statistics [13-17]. These approaches provide powerful tools for quantifying probabilities of unlikely outcomes, but they do not directly address the role of historical accumulation in defining event significance. In particular, a rare event is not necessarily anomalous in an informational sense: depending on context, it may be expected, neutral, or even irrelevant. This distinction highlights the need for observables that explicitly incorporate memory and historical reference into anomaly detection.

In this work, we introduce *luck* as an informational observable designed to quantify historical mismatch. Luck is not interpreted as a subjective notion, nor as a synonym of rarity or favorable outcome. Instead, it is defined as a quantitative measure of how much an event deviates from what the accumulated history of the system would suggest, from the perspective of an observer. By construction, luck is undefined in the absence of history, reflecting the fundamental principle that anomalies require memory.

The framework proposed here is intentionally minimal. Luck is defined directly in terms of probability and its cumulative accumulation, without introducing external thresholds, training phases, or model-specific tuning parameters. By normalizing luck, we obtain a distribution over events that describes how unexpected information is allocated within a process, and the associated entropy of luck provides a compact global descriptor of informational structure [1, 4, 18]. In this sense, anomaly detection is reframed as a problem of informational allocation rather than local statistical deviation.

The aim of this article is conceptual and preliminary. We focus on clarifying the definition and interpretation of luck, outlining its basic mathematical properties, and illustrating its behavior through synthetic examples inspired by noisy systems with intermittent events. Rather than proposing a complete theory or exhaustive empirical validation, this work establishes a foundational framework that complements existing approaches to rare events and anomaly detection in systems with memory [13-20].

CONCEPTUAL DEFINITION OF LUCK

LUCK, PROBABILITY, AND RARITY

In everyday language, luck is often associated with rare or favorable events. However, rarity alone is insufficient to define luck in a precise or operational way. A rare event may be fully expected within a given context, while a relatively common event may become highly significant if it contradicts strong prior expectations. Probability quantifies how often events occur within a model, but it does not by itself determine their informational relevance.

In this work, luck is explicitly distinguished from both probability and rarity. Probability describes frequency within a probabilistic description of a system, whereas rarity refers to the smallness of that probability. Luck, in contrast, is introduced as an informational quantity that measures how much an event deviates from what the accumulated history of the system would suggest. An event is therefore not considered “lucky” because it is rare, but because it carries disproportionately large informational impact relative to historical expectations.

This distinction is essential. In many systems characterized by heavy-tailed statistics or correlated noise, rare events may be common enough to lose discriminative power. Luck, as defined here, aims to identify events that reorganize the informational structure of the process rather than merely occupying the tail of a distribution.

OBSERVER DEPENDENCE AND CONTEXT

Luck is inherently observer-dependent. Whether an event is considered significant depends on how the observer defines the system, which variables are monitored, and what constitutes prior knowledge. For example, in a dice game, all outcomes may have equal probability, yet only certain outcomes are considered relevant or “lucky” depending on the rules of the game. The same event may therefore be informationally significant or insignificant depending on context.

In the present framework, observer dependence enters through the construction of the probability representation itself. The probability $p(x)$ reflects the observer’s description of the system, and the accumulation of probability over time encodes the observer’s historical expectations. Luck does not impose an external notion of favorability or utility; instead, it quantifies deviation from accumulated expectation within a given observational framework.

This perspective avoids normative interpretations of luck. The observable introduced here does not distinguish between “good” or “bad” events, but between events that are consistent with history and events that break historical patterns.

SYSTEMS WITH MEMORY AND THE ROLE OF HISTORY

A central premise of this work is that anomalies require memory. In the absence of historical information, no event can be meaningfully described as anomalous, since there is no reference against which it can be evaluated. Systems with memory accumulate information over time, and it is this accumulation that allows deviations to be detected.

Luck is therefore undefined when no history exists. This is not a technical limitation, but a conceptual feature of the observable. An event becomes informative only insofar as it contradicts or reshapes what has already been observed. In this sense, luck measures historical mismatch rather than instantaneous deviation.

This property makes luck particularly suited to non-stationary systems, where local statistics fluctuate strongly and where the relevance of an event depends on long-term trends rather than short-term variability.

OPERATIONAL DEFINITION

Let $x$denotes an ordered index representing the progression of a system. In most applications x corresponds to time, but more generally it may represent any monotonic ordering variable such as event number or cumulative count. Let $p(x)$ denotes the probability or probability density associated with observing the system state at index x. Importantly, $p(x)$ does not represent the probability of time itself, but the probability of the observed state conditioned on the chosen description of the system.

We define luck as

$$L(x) = \frac{p(x)}{\int_0^x p(s)\, ds}. \quad (1)$$

The denominator represents the cumulative probability accumulated by the system up to index x, providing a historical reference. Luck therefore quantifies the relative contribution of the present observation with respect to the entire past. High values of $L(x)$ correspond to events whose probability is disproportionately large compared to what the accumulated history would suggest, while low values indicate events consistent with historical expectations.

By construction, luck is dimensionless and undefined in the absence of history. It should not be interpreted as a probability or frequency, but as an informational observable derived from probability and its accumulation.

MATHEMATICAL PROPERTIES AND INTERPRETATION

This section summarizes the basic mathematical properties of luck and clarifies its informational interpretation. The emphasis is not on formal derivations, but on understanding what the observable measures and under which conditions it is well defined.

INFORMATIONAL INTERPRETATION

Let

$$P(x) = \int_0^x p(s)\, ds, \quad (2)$$

denotes the cumulative probability accumulated by the system up to index x. Provided that $P(x) > 0$, the definition of luck can be rewritten as

$$L(x) = \frac{p(x)}{P(x)} = \frac{d}{dx} \ln P(x). \quad (3)$$

This representation highlights the informational character of luck. It shows that luck corresponds to the local growth rate of the logarithm of accumulated probability. In other words, luck measures how rapidly new probabilistic information is added relative to what the system has already accumulated. Events with large luck values are those that induce abrupt changes in the historical accumulation, while events with small luck values are consistent with established trends.

This interpretation distinguishes luck from probability itself. While probability quantifies the likelihood of observing an event, luck quantifies the informational impact of that observation relative to the past.

REGULARIZATION AND EXISTENCE

At the early stages of a process, the cumulative probability $P(x)$ may be arbitrarily small. In such cases, large values of $L(x)$ may arise purely from the absence of sufficient historical information rather than from genuinely anomalous events. To avoid this artifact, a minimal historical scale is introduced.

Specifically, we define a regularized cumulative probability

$$P_\varepsilon(x) = \int_\varepsilon^x p(s)\, ds, \quad (4)$$

where $\varepsilon > 0$ represents the smallest meaningful memory horizon of the system. The corresponding regularized luck is then

$$L_\varepsilon(x) = \frac{p(x)}{P_\varepsilon(x)}. \tag{5}$$

This regularization ensures that luck is evaluated only once a minimal amount of history has been accumulated. The parameter εdoes not introduce an arbitrary anomaly threshold; instead, it encodes the requirement that anomalies cannot be defined before the system has developed a reference history.

DISCRETE FORMULATION

Many practical applications involve discrete events rather than continuous signals. For a sequence of events indexed by $i = 1, 2, ..., N$, with associated probabilities p_i, the cumulative probability up to event i is:

$$P_i = \sum_{j<i} p_j. \tag{6}$$

Luck in the discrete case is defined as

$$L_i = \frac{p_i}{P_i}. \tag{7}$$

This discrete formulation is directly applicable to empirical time series, event catalogs, and numerical simulations. As in the continuous case, luck is undefined for the first event and becomes meaningful only once historical accumulation exists.

SUMMARY OF PROPERTIES

The main properties of luck can be summarized as follows:

1.) Luck is dimensionless and derived from probability and its accumulation.
2.) Luck is undefined in the absence of history, reflecting the principle that anomalies require memory.
3.) High luck values correspond to events that produce large informational changes relative to accumulated expectations.
4.) The observable is non-local in time, as it depends on the entire past rather than on short-time windows.

These properties make luck particularly suitable for analyzing noisy, non-stationary systems in which local statistical measures fail to capture historical significance.

NORMALIZED LUCK AND ENTROPY

The local definition of luck introduced in the previous sections allows the identification of history-breaking events at the level of individual observations. To characterize the global informational structure of a process, it is necessary to analyze how luck is distributed across all events. This is achieved by introducing a normalized luck field and its associated entropy.

NORMALIZED LUCK AS INFORMATIONAL ALLOCATION

Given a sequence of events indexed by i, with corresponding luck values L_i, we define the normalized luck as

$$\tilde{L}_i = \frac{L_i}{\sum_j L_j}. \tag{8}$$

By construction, $\tilde{L}_i \geq 0$ and

$$\sum_i \tilde{L}_i = 1. \tag{9}$$

Normalized luck therefore defines a probability distribution over events. Unlike the original probability p_i, which reflects how often events occur, normalized luck reflects where unexpected information is generated within the process.

This distinction is essential. Events that are frequent or locally prominent may contribute little to the overall informational structure if they are consistent with accumulated history. In contrast, events with large normalized luck concentrate a disproportionate fraction of the total unexpected information and correspond to genuinely anomalous, history-breaking observations.

INFORMATIONAL INTERPRETATION

Normalized luck provides a natural ranking of events according to their informational relevance. Most events typically contribute negligibly to the total informational content, while a small subset dominates the distribution. In this framework, anomalies are not defined by a binary criterion, but emerge naturally as the top contributors to normalized luck.

This ranking-based perspective avoids the need for externally imposed thresholds or labels. Instead of classifying events as anomalous or non-anomalous, the framework identifies events according to how strongly they reorganize the historical expectations of the system.

ENTROPY OF LUCK

To quantify how informational contributions are distributed across the process, we define the entropy of luck as

$$H_L = -\sum_i \tilde{L}_i \ln \tilde{L}_i. \tag{10}$$

For comparison across systems of different sizes, we introduce the normalized entropy

$$\widehat{H}_L = \frac{H_L}{\ln N}, \tag{11}$$

where N is the total number of events. By construction, $0 \le \widehat{H}_L \le 1$.

The entropy of luck measures the degree of concentration of informational contributions. High entropy indicates that information is evenly distributed across events, while low entropy indicates that information is concentrated in a small number of observations.

DETERMINISM, STOCHASTICITY, AND INTERMITTENCY

The entropy of luck provides a compact diagnostic of system behavior:

- When $\widehat{H}_L \approx 1$, normalized luck is approximately uniform. Informational contributions are evenly distributed, indicating regular or quasi-deterministic dynamics in which history reliably anticipates future behavior.
- When $\widehat{H}_L \ll 1$, normalized luck is strongly concentrated. Informational contributions are dominated by a small number of events, indicating intermittent dynamics characterized by rare, history-breaking anomalies.
- Intermediate values of $\widehat{H}_L$ correspond to mixed regimes, where regular behavior coexists with intermittent deviations.

This interpretation allows the identification of regime changes without invoking explicit anomaly thresholds. Transitions between regimes manifest as changes in the concentration of normalized luck rather than as abrupt changes in local statistics.

SUMMARY

Normalized luck transforms local measurements of historical mismatch into a global informational structure. Together with its associated entropy, it provides a principled way to distinguish between regular, stochastic, and intermittent regimes. These quantities form the basis for the illustrative examples presented in the following section, where their behavior is examined in noisy systems with intermittent events.

EXAMPLES AND ILLUSTRATIVE APPLICATIONS

In this section, we illustrate the proposed framework using synthetic signals designed to mimic noisy systems with intermittent events. The purpose of these examples is not empirical validation, but to clarify how luck, normalized luck, and the entropy of luck behave in controlled yet realistic conditions, and how they differ from classical local anomaly detectors.

NOISY PROBABILISTIC SIGNAL WITH INTERMITTENT EVENTS

Figure 1 shows the synthetic probability signal used as input for the analysis. The signal consists of a smooth background component combined with strong additive noise and a small number of injected events. Such a construction is representative of many real-world systems in which meaningful events are embedded in highly.

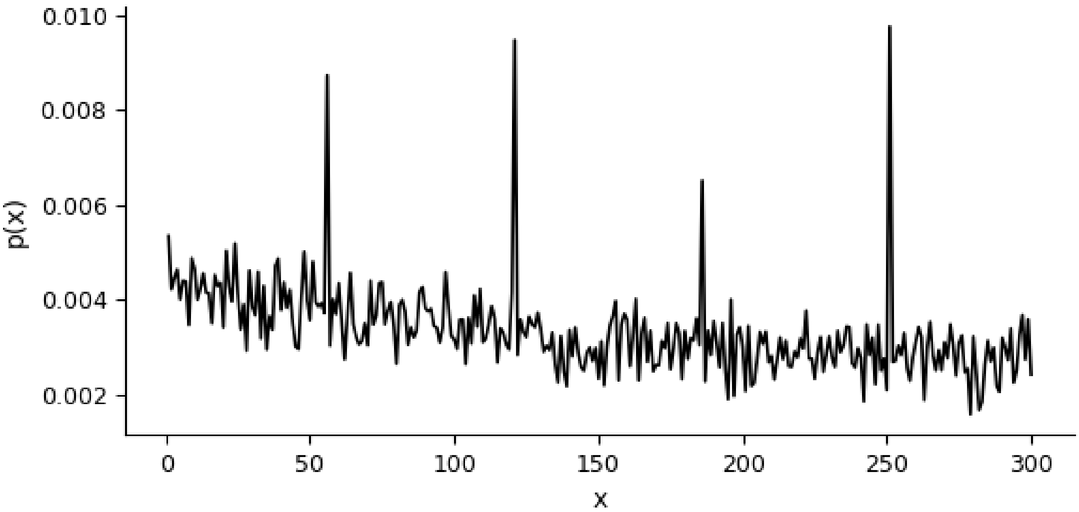

Figure 1. Noisy probability signal used as input for anomaly detection. The time series contains a smooth background component, strong additive noise, and a small number of injected high-amplitude events. Local fluctuations dominate the signal, making events of interest difficult to identify using probability alone.

In the raw probability representation, local fluctuations dominate the signal. Although large events are present, their identification based solely on probability is ambiguous and strongly dependent on the choice of arbitrary thresholds or window sizes. This makes the signal a suitable test case for history-dependent anomaly detection.

LUCK AS A HISTORY-BASED TRANSFORMATION

Figure 2 shows the corresponding luck computed from the probability signal in Figure 1, using the definition introduced in the second section. A clear qualitative transformation is observed. Background noise is strongly suppressed, while events that deviate significantly from the accumulated history appear as sharp, isolated peaks.

This behavior reflects the non-local nature of luck. Short-lived fluctuations that dominate the probability signal do not significantly affect luck, as they contribute little relative to the accumulated historical probability. In contrast, events whose probability is disproportionately large compared to past observations produce pronounced peaks, signaling history-breaking behavior.

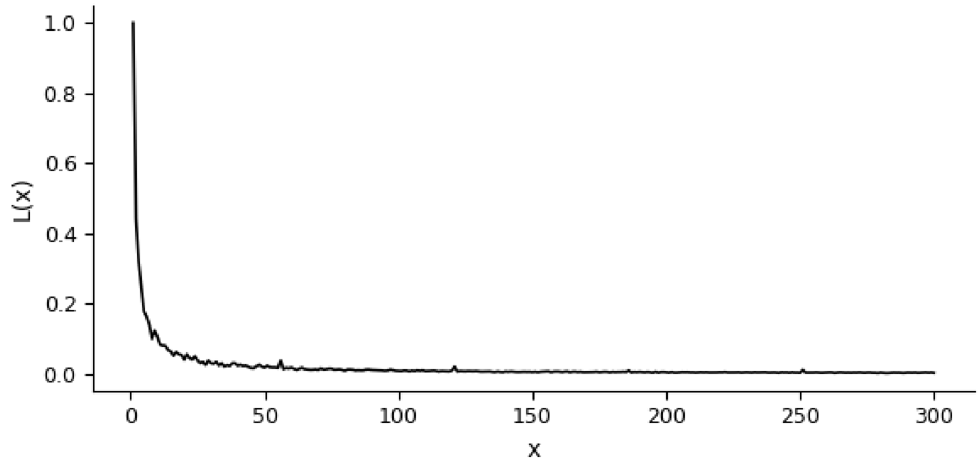

Figure 2. Luck computed from the noisy probability signal shown in Figure 1. Background noise is strongly suppressed, while events that deviate significantly from the accumulated history appear as sharp, isolated peaks. The initial stage is regularized to avoid non-physical divergence in the absence of historical information.

COMPARISON WITH LOCAL STATISTICAL DETECTORS

To highlight the difference between history-based and local approaches, Fig. 3 compares luck with the positive part of a rolling z-score computed from the same probability signal. The z-score responds to local variance and produces multiple peaks associated with noise-driven fluctuations. As a result, distinguishing genuinely significant events from background variability requires additional tuning or thresholds.

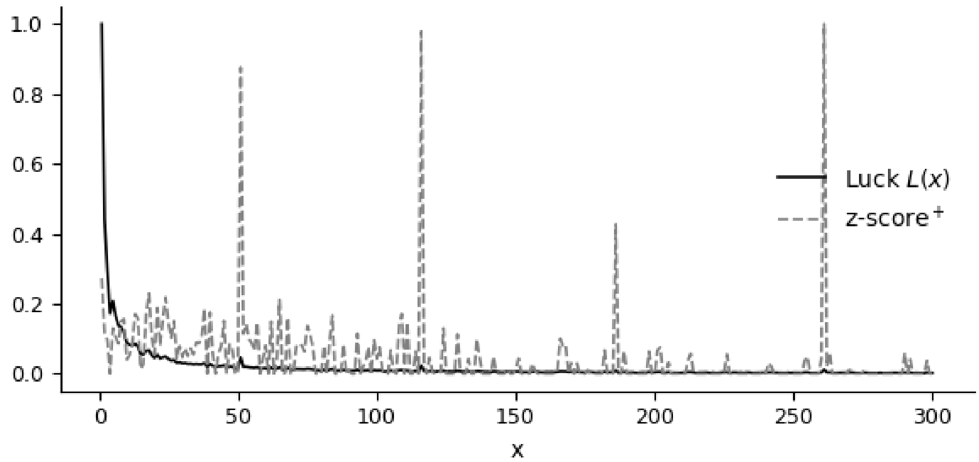

Figure 3. Comparison between luck $L(x)$and the positive part of a rolling z-score applied to the same probability signal. The z-score responds to local variance and produces multiple peaks associated with noise-driven fluctuations, whereas luck highlights a small number of dominant events that significantly deviate from the accumulated history of the system.

Luck, by contrast, produces a small number of dominant peaks corresponding to events that significantly reorganize the accumulated history. This comparison illustrates that luck-based detection encodes information accumulated over the entire past, rather than relying on short sliding windows, making it more robust in noisy and non-stationary settings.

NORMALIZED LUCK AND INFORMATIONAL CONCENTRATION

Figure 4 displays the normalized luck distribution associated with the signal. The distribution is highly uneven: most events contribute negligibly to the total informational content, while a small subset concentrates a large fraction of normalized luck.

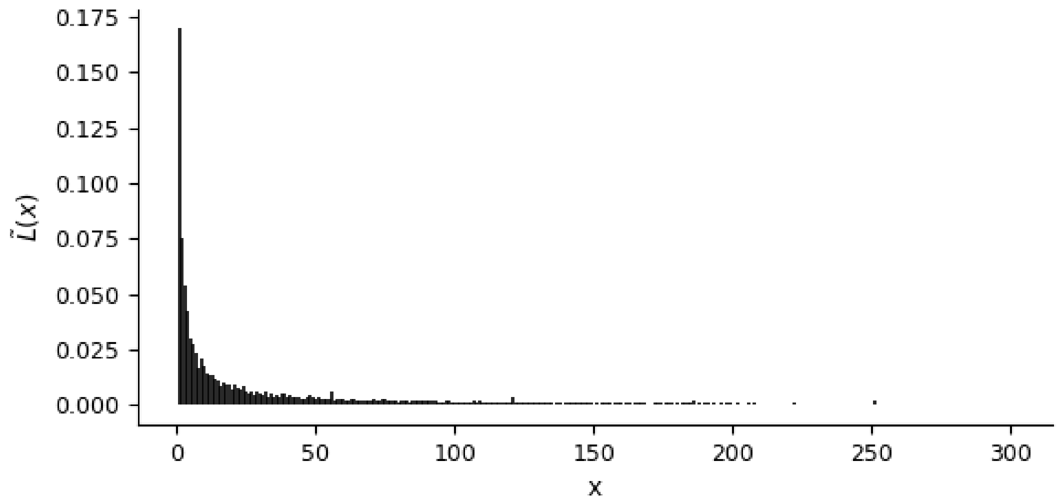

Figure 4. Normalized luck distribution, representing the fraction of total unexpected information contributed by each event. Most events contribute negligibly, while a small subset concentrates a large fraction of the informational content, indicating the presence of history-breaking observations rather than random fluctuations.

This result supports a central conceptual point of the framework. Anomalies are not defined by rarity alone, but by the concentration of unexpected information. Even in signals with many fluctuations, only events that strongly contradict accumulated history dominate normalized luck.

ENTROPY OF LUCK AND REGIME IDENTIFICATION

Figures 5 and 6 show the local contribution to the entropy of luck and its sliding-window normalized value, respectively. The same events identified as dominant peaks in luck also dominate the entropy, while the remainder of the process contributes little from an informational perspective.

Periods of high normalized entropy correspond to regular or quasi-deterministic behavior, in which informational contributions are broadly distributed. In contrast, pronounced entropy drops coincide with the emergence of dominant events, indicating intermittent regimes in which a small number of observations carry most of the informational content.

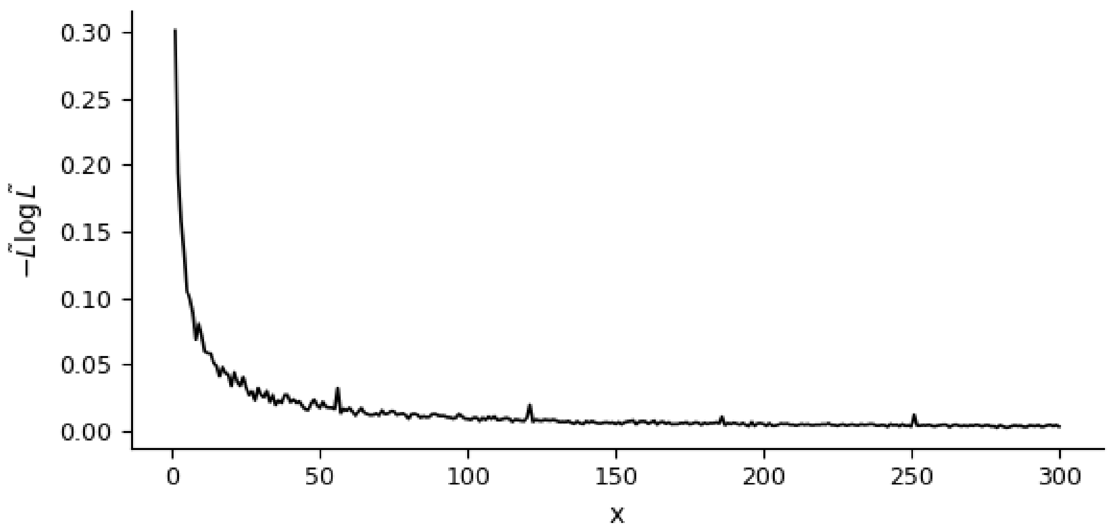

Figure 5. Local contribution to the entropy of luck. The same events identified as dominant informational contributors concentrate most of the entropy, while the remainder of the process is largely informationally redundant.

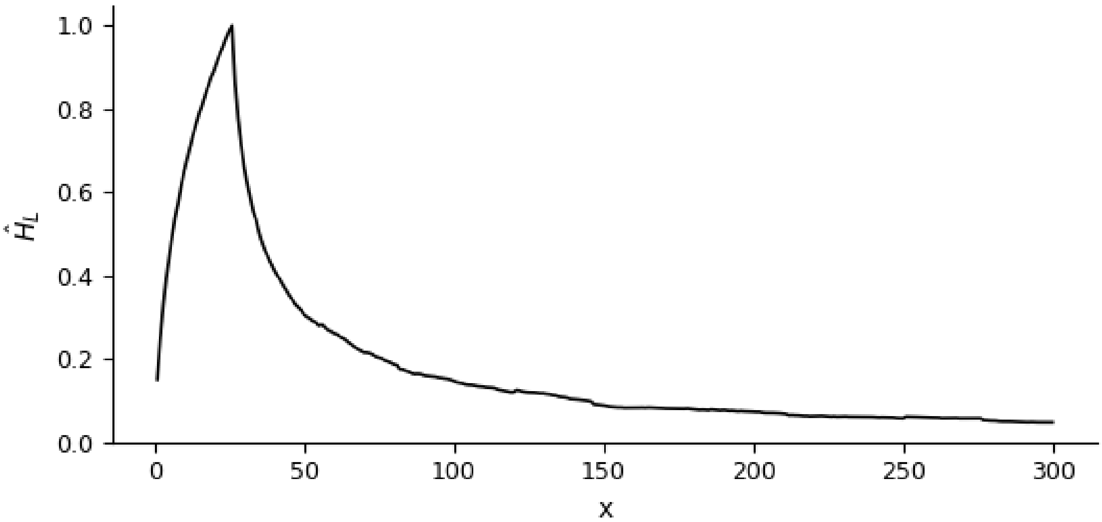

Figure 6. Sliding-window normalized entropy of luck. High entropy values correspond to regular or quasi-deterministic behavior with distributed informational contributions, whereas pronounced entropy drops signal intermittent regimes dominated by a small number of informationally dominant events.

ILLUSTRATIVE EARTHQUAKE-LIKE EXAMPLE

As an illustrative example, we consider a synthetic earthquake-like signal composed of a noisy background of small events and a few large energy releases. Figure 7 shows the probability representation derived from this signal, which is strongly fluctuating and does not trivially distinguish major events from background activity.

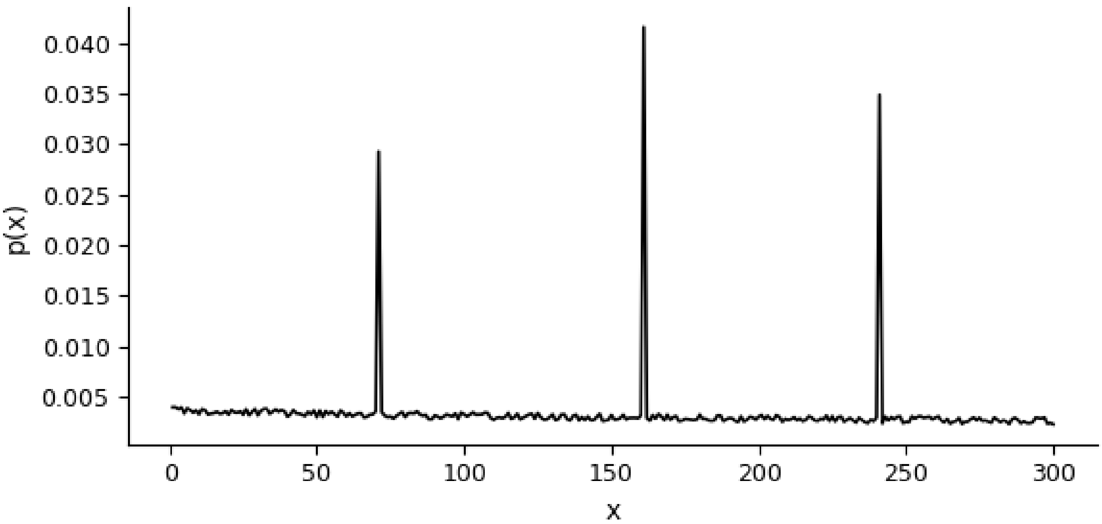

Figure 7. Synthetic earthquake-like example. Probability mass derived from a noisy background of small events and a few large energy releases. Although the raw signal is strongly fluctuating, major events are not trivially distinguishable using probability alone.

Figure 8 shows the corresponding luck computed for this example. From a detection perspective, large events appear as informationally dominant, standing out clearly against the accumulated background. In this context, the term *luck* is used strictly as an informational observable and does not carry any normative or favorable connotation. The example demonstrates that the framework naturally highlights rare, history-breaking events in systems characterized by long quiescent periods and intermittent large releases.

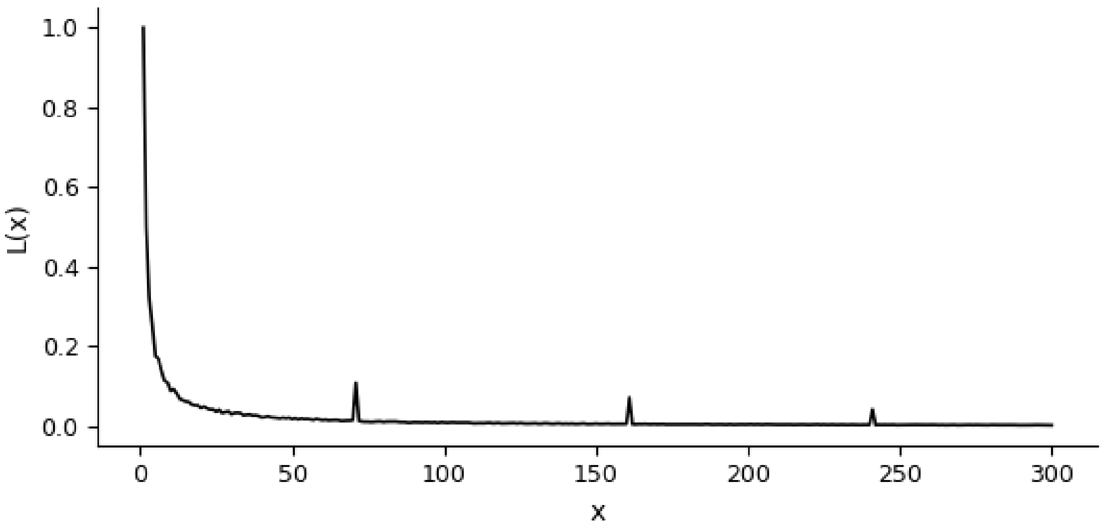

Figure 8. Luck computed for the earthquake-like example shown in Figure 7. Large events appear as informationally dominant relative to the accumulated background. The term "luck" is used here strictly as an informational observable and carries no normative or favorable connotation.

DISCUSSION

The framework introduced in this work reframes anomaly detection as a problem of historical information mismatch rather than local statistical deviation. By construction, luck depends on the accumulated history of the system and is therefore inherently non-local in time. This property distinguishes it from classical detectors based on sliding windows, thresholds, or instantaneous variance, which often struggle in noisy and non-stationary environments.

A key conceptual aspect of luck is its observer dependence. The observable does not encode notions of favorability or utility, but instead quantifies deviation from accumulated expectation within a chosen probabilistic description. Different observers, using different probability representations or system variables, may therefore assign different luck values to the same event. This dependence is not a limitation, but a necessary feature of any informational measure, as information is intrinsically relational.

The examples presented illustrate that luck suppresses background fluctuations while selectively amplifying events that reorganize the historical structure of the process. Importantly, these events are not necessarily the rarest ones, but those that concentrate a disproportionate fraction of unexpected information. This distinction clarifies the conceptual difference between luck and rarity and addresses a common ambiguity in the interpretation of extreme or infrequent events.

The entropy of luck provides a complementary global perspective. Rather than identifying individual anomalies, it characterizes how informational contributions are distributed across the process. High entropy corresponds to regular regimes in which history reliably anticipates future behavior, while low entropy signals intermittent regimes dominated by a small number of history-breaking events. In this sense, regime changes can be detected as changes in informational concentration rather than as abrupt shifts in local statistics.

As a preliminary report, this work does not attempt to establish a direct equivalence between luck and existing theoretical frameworks such as large deviation theory or extreme value statistics. While conceptual connections are evident, a systematic comparison lies beyond the scope of the present study. Similarly, the examples considered here are synthetic and illustrative. Empirical validation will require application to real-world datasets and comparison with independent markers of structural change or external event catalogs.

Finally, the simplicity of the framework is worth emphasizing. Luck is computed using only probability and its cumulative accumulation, without training phases, tuning parameters, or externally imposed thresholds. This makes the approach computationally efficient and suitable for exploratory analysis in systems where historical context plays a central role.

CONCLUSIONS

In this work, we introduced luck as an informational observable designed to quantify historical mismatch in systems with memory. Defined as the ratio between local probability and cumulative historical probability, luck is undefined in the absence of history and becomes meaningful only once a system has accumulated experience. This property reflects a fundamental principle: anomalies require memory.

By normalizing luck, we obtained a distribution that describes how unexpected information is allocated across events. The associated entropy of luck provides a compact global descriptor of informational structure, distinguishing between regular, quasi-deterministic regimes and intermittent, anomaly-dominated dynamics. In this framework, anomalies are not defined by rarity alone, but by their disproportionate contribution to historical information.

Through synthetic examples with strong noise and intermittent events, we showed that luck-based analysis robustly suppresses background fluctuations while highlighting history-breaking observations. Comparisons with local statistical detectors illustrate the advantages of a history-dependent approach in non-stationary environments.

Overall, the proposed framework offers a conceptually clear and computationally simple perspective on anomaly detection, emphasizing informational allocation rather than local deviation. As a preliminary contribution, it establishes a foundation for future work on extensions to multivariate systems, finite-memory kernels, and empirical applications across physical, social, and institutional domains.

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