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New Features of Permutation Entropy in Ordinal Patterns Complexity Plane

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Abstract

Time series analysis plays a vital role in understanding the underlying dynamics of complex systems across various domains such as engineering, economics, and the physical sciences. Traditional approaches, namely time-domain and frequency-domain methods often rely on strong assumptions such as stationarity, large sample sizes, or normality, which are frequently violated in real-world data. As a robust alternative, Bandt and Pompe [5] introduced a non-parametric method based on ordinal pattern symbolization and information theoretic descriptors. This approach transforms local segments of the time series into rank-based symbols, constructs a histogram of ordinal patterns, and computes permutation entropy, offering resistance to noise and model independence. Building on this, Lamberti et al [20]. introduced statistical complexity, allowing the joint representation of entropy and complexity in the entropy-complexity plane. This proposal investigates the use of permutation entropy and statistical complexity for time series analysis, focusing on pattern histogram construction, descriptor estimation, and confidence interval evaluation. The goal is to assess the statistical properties and practical utility of these measures for analyzing nonlinear, noisy, and nonstationary time series data.

Contents

Chapter 1

Introduction

Time series contain valuable insights about the underlying system that generates the data. Their analysis is typically conducted using two primary approaches: time-domain and transformed-domain methods. In the context of time-domain analysis, Bandt and Pompe [5] introduced a novel methodology that is non-parametric and rooted in information theory descriptors: Ordinal Patterns symbolization.

Bandt and Pompe [5] proposed transforming small subsets of the time series observations into symbols that encode the sorting properties of the values in these subsets. Then, they computed a histogram of those symbols. The resulting distribution is less sensitive to outliers compared to the original data, and the histogram is independent of any specific model. The proposal proceeds by computing descriptors from this histogram, and extracting information about the system from these descriptors. As a result, this approach is versatile and applicable to a wide range of scenarios.

This study explores features derived from Bandt and Pompe symbolization, specifically Shannon entropy, complexity, and represents them graphically in the entropy-complexity plane, which is represented as a point in the $\mathbb{R}^2$ manifold. This proposal focuses on the independent analysis of permutation entropy and ordinal patterns in time series analysis. It involves calculating pattern histograms, entropy, complexity, and confidence intervals to better understand the statistical properties of these tools. Additionally, the role of confidence intervals in entropy and complexity, along with their applications in time-series clustering, will be explored. Future work will expand to include alternative measures, such as Rényi entropy, Tsallis entropy and Fisher information, with a focus on deriving confidence intervals for their entropy and complexity under the Multinomial model.

Time series analysis is widely applied across various fields, including engineering, economics, physical sciences, and more. A time series is defined as a collection of observations x_t, each representing a realized value of a particular random variable X_t, where time can be either discrete or continuous.

Examples of time series applications include finance (e.g., analyzing exchange rate movements or commodity prices), biology (e.g., modeling the growth and decline of bacterial populations), medicine (e.g., tracking the spread of diseases like COVID-19 or influenza), and geoscience (e.g., predicting wet or dry days based on past weather conditions).

The primary goal of time series analysis is to understand the nature of the phenomenon represented by the observed sequence. Time domain and frequency domain methods are the two primary approaches used in time series analysis. The temporal approach relies on concepts such as auto-correlation and regressions, where a time series' present value is analyzed in relation to its own past values or the past values of other series. This method represents time series directly as a function of time. On the other hand, the spectral approach represents time series through spectral expansions, such as wavelets or Fourier modes [57].

However, these methods often require assumptions such as large sample sizes or normally distributed observations that are rarely met in real-world empirical data. For many statistical techniques to be valid, these assumptions must hold, but in practice, they are frequently violated.

For example, traditional approaches to time series analysis, such as time domain and frequency domain methods, rely on assumptions that are not always valid in real-world data. The time domain approach, which uses techniques like auto-correlation and regression, assumes stationary and often struggles with nonlinear or non-stationary data. Similarly, the frequency domain approach, which represents time series through spectral expansions such as wavelets or Fourier modes, may require assumptions about periodicity and may not effectively capture short-term fluctuations.

Many statistical methods in these approaches depend on specific conditions, such as large sample sizes or normally distributed observations. However, these assumptions are often unrealistic, leading to inaccurate or biased results. When such conditions are not met, alternative methods must be considered.

As a result, alternative methods, often referred to as non-parametric techniques, must be considered. These methods rely on the rank R_t of the observations x_t rather than their actual values, making them robust and applicable to a wide range of data sets. Since non-parametric tests do not assume a normal distribution, they are highly reliable. For example, the Kruskal-Wallis H test and the Wilcoxon test are effective tools for comparing two or more population probability distributions from independent random samples. However, these techniques are not always suitable for time series data, which often require specialized methods tailored to their unique characteristics.

To address these challenges, ordinal pattern methods provide a robust alternative. Instead of analyzing the absolute values of a time series, these methods focus on the order relationships among consecutive data points.

This approach effectively captures the underlying dynamics of complex systems and offers several advantages.

The ordinal pattern-based method has become a widely used tool for characterizing complex time series. Since its introduction nearly twenty-three years ago by Bandt and Pompe in their foundational paper [5], it has been successfully applied across various scientific fields, including biomedical signal processing, optical chaos, hydrology, geophysics, econophysics, engineering, and biometrics. It has also been used in the characterization of pseudo-random number generators.

The Bandt and Pompe method successfully analyzes time series by transforming them into ordinal patterns, constructing a histogram, and computing Shannon entropy, making it robust against outliers and independent of predefined models.

Later, Rosso [47] introduced an additional dimension to this analysis Statistical Complexity derived from the same histogram of causal patterns.

Introduction to Ordinal Pattern Analysis

Ordinal patterns are a non-parametric representation of real-valued time series and ordinal patterns are transformations that encode the sorting characteristics of values in $\mathbb{R}^D$ into $D!$ symbols, where D represents for the "Embedding Dimension" and usually ranges between three to six. One of the possible encoding is the set of indexes that sort the D values in non-decreasing order.

To illustrate this idea, let $\boldsymbol{x} = \{x_1, x_2, \ldots, x_{(n+D-1)}\}$ be a real valued time series of length $n + D - 1$ without ties. If the $\boldsymbol{x}$ takes infinitely many values, it is common to replace them with a symbol sequence $\boldsymbol{\pi} = (\pi_1, \pi_2, \ldots, \pi_n)$ consisting of finitely many symbols and then compute the entropy from this sequence. The corresponding symbol sequence naturally emerges from the time series without requiring any model assumptions. We compute $\boldsymbol{\pi} = (\pi_1, \pi_2, \ldots, \pi_n)$ symbols from sub-sequences of embedding dimension D. There are $D!$ possible symbols: $\pi_j \in \boldsymbol{\pi} = (\pi^1, \pi^2, \ldots, \pi^{D!})$. The histogram of proportions $h = (h_1, h_2, \ldots, h_{D!})$ in which the bin h_ℓ is the proportion of symbols of type π^ℓ of the total number of symbols. For convenience, we will model those symbols as a k dimensional random vector where $k = D!$.

Problem Statement

To illustrate this concept, imagine tracking the mean monthly humidity in Wellington. You want to analyze how humidity changes throughout the year. By examining this data, you can uncover interesting patterns that highlight the variations in humidity across different months.

Month	Mean of relative humidity
January	77.3
February	81.0
March	82.4
April	81.7
May	83.6
June	85.6
July	84.4
August	83.1
September	78.8
October	79.6
November	78.2
December	78.8

Table 1.1: Mean monthly humidity variations in Wellington throughout the year

Mean monthly humidity in Wellington is shown in Figure 1.1.

We can convert this actual data into ordinal patterns. To do this, for each month, we determine the order of the humidity values rather than their actual magnitudes. Each three-time-point sequence (which can be adjusted based on preference) is converted into an ordinal pattern. This "embedding dimension" usually varies between 3 and 6, but any dimension is possible. The conversion can be made in any way that uniquely maps the sorting properties of the sub sequence into a symbol. For example, consider the

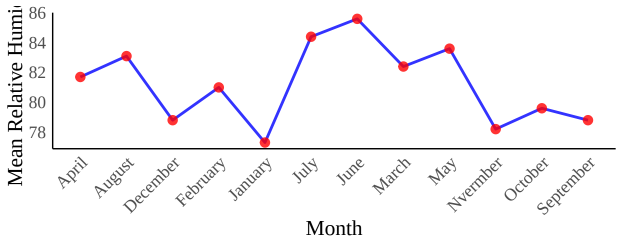

Figure 1.1: Mean Monthly humidity in Wellington

time series presented in Table 1.1. We can transform this series into ordinal patterns as follows. Assume we use patterns of length $D = 3$ with a time lag $\tau = 1$. The first overlapping window $(77.3, 81, 82.4)$ corresponds to the pattern $(1, 2, 3)$, where type is considering with the order of the real time series data. Here 77.3 is the smallest value and is assigned rank 1; 81 is the next highest and is assigned rank 2; and 82.4 is the largest, assigned rank 3. As another example, consider the overlapping window $(83.1, 78.8, 79.6)$. In this case, 78.8 is the smallest value and is assigned rank 1; 79.6 is the next highest, assigned rank 2; and 83.1 is the largest, assigned rank 3. Therefore, the pattern for this window is $(3, 1, 2)$. Table 1.2 has shown this scenario.

t	Mean Humidity sequence	Ordinal Pattern
1	(77.3,81,82.4)	$(123) = \pi^1$
2	(81,82.4,81.7)	$(132) = \pi^2$
3	(82.4,81.7,83.6)	$(213) = \pi^3$
4	(81.7,83.6,85.6)	$(123) = \pi^1$
5	(83.6,85.6,84.4)	$(132) = \pi^2$
6	(85.6,84.4,83.1)	$(321) = \pi^6$
7	(84.4,83.1,78.8)	$(321) = \pi^6$
8	(83.1,78.8,79.6)	$(312) = \pi^5$
9	(78.8,79.6,78.2)	$(231) = \pi^4$
10	(79.6,78.2,78.8)	$(312) = \pi^5$

Table 1.2: Ordinal Patterns

As shown in Table 1.2, we have six mutually exclusive events which we denote as $\{\pi^1, \pi^2, \ldots, \pi^6\} = \{(123), (132), (213), (231), (312), (321)\}$. The probability distribution of the mean humidity is calculated based on ordinal patterns as given below.

$$\hat{p}_i = \frac{\#\{\pi_j \in \boldsymbol{\pi} : \pi_j = \pi^i\}}{n}; 1 \leq i \leq 6, \tag{1.1}$$

where $\hat{\boldsymbol{p}} = (\hat{p}_1, \ldots, \hat{p}_6)$.

Notation	Probability
$p(\pi^1)$	$\frac{2}{10}$
$p(\pi^2)$	$\frac{2}{10}$
$p(\pi^3)$	$\frac{1}{10}$
$p(\pi^4)$	$\frac{1}{10}$
$p(\pi^5)$	$\frac{2}{10}$
$p(\pi^6)$	$\frac{2}{10}$

Table 1.3: Probability function

We construct the histogram of proportions $h = (h_1, h_2, h_3, h_4, h_5, h_6)$, where each bin h_ℓ represents the proportion of symbols of type π^ℓ out of the total six symbols. The histogram graph is shown Figure 1.2.

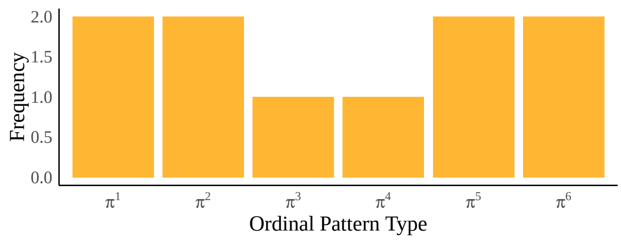

Figure 1.2: Histogram of proportions of the observed patterns according to Table 1.3.

This example explains how time series data can be converted into ordinal patterns and how the probability distribution function can be calculated from these patterns. Chapter Two will review the literature on ordinal pattern analysis, while Chapter Three will expand on this concept by exploring the characterization of time series. It will also cover the computation of two key descriptors entropy and complexity from the resulting histograms. Additionally, Chapter Three will outline the main ideas and objectives of this research project.

Chapter 2

Literature Review

This chapter primarily focuses on reviewing the literature related to this research. In addition, we analyze R packages that compute entropy and complexity, including those not available on CRAN. We also examine any limitations or restrictions associated with these packages.

2.1 Preliminaries

Waschke et al. [60] investigated how the hippocampus encodes sensory information during memory formation by analyzing time series data from single-neuron recordings in 34 human patients undergoing neurosurgical procedures. Using permutation entropy, a measure of temporal complexity, they quantified trial-to-trial variability in neuronal spiking activity during a visual memory task. Their analysis revealed that hippocampal neurons dynamically track the richness of visual input, with greater spiking variability corresponding to more complex or information-rich stimuli. Key features of the study include the use of intracranial single-neuron recordings in humans, the application of entropy-based metrics to capture neural variability, and the discovery that this variability not only reflects stimulus content but also predicts subsequent memory performance, highlighting the role of variability as a functional marker of memory encoding.

Another study by Alessio Perinelli and Leonardo Ricci [39] aimed to develop a statistically grounded method to evaluate the temporal stationarity of resting-state EEG data using permutation entropy (PE). Researchers analyzed EEG recordings from the LEMON dataset, involving young and elderly adults, during alternating eyes-open (EO) and eyes-closed (EC) conditions. EEG signals were source-reconstructed into 30 brain regions, segmented, and assessed for entropy-based stability using a chi-square test on PE values. Key findings revealed greater nonstationarity in elderly participants and in EC conditions, with unstable segments showing higher PE, indicating increased signal complexity. This method provides a reliable framework for identifying unstable EEG periods and has potential applications in clinical diagnostics and real-time neural monitoring.

Li et al. [26] discussed the Multiscale Grayscale Dispersion Entropy (MGDE) model, an advanced entropy-based metric designed to assess the complexity of time series data across multiple temporal scales. Building upon the foundation of Grayscale Dispersion Entropy (GDE), MGDE incorporates a multiscale framework that enables a more comprehensive analysis of dynamic behaviors in time series. The methodology involves applying a coarse-graining process to the original time series data, followed by the computation of GDE at each scale, effectively capturing the signal's complexity at various temporal resolutions. Key findings from the study demonstrate that MGDE effectively distinguishes between different types of signals, including white Gaussian noise, $1/f$ noise, and chaotic signals, highlighting its robustness and sensitivity to underlying dynamics. The research also emphasizes MGDE's computational efficiency and its potential applicability in real-time signal processing. Looking ahead, MGDE holds significant promise for diverse applications in fields such as biomedical engineering, finance, and environmental science, where understanding the multiscale complexity of time series data is essential.

The article titled "Detection of Ship Echo Signals in Reverberation Background Based on Sample Entropy and Multiscale Sample Entropy" by Li et al. [23], addresses the challenge of detecting ship echo signals amidst reverberation in underwater environments. Traditional frequency-based detection methods often struggle under conditions of low signal-to-reverberation ratios (SRR) and minimal Doppler shifts. To overcome these limitations, the authors introduce entropy-based approaches, specifically, Sample Entropy (SampEn) and Multiscale Sample Entropy (MSE), to analyze the complexity differences between target echoes and reverberation noise. Through simulations under various SRR and Doppler shift scenarios, the study demonstrates that while frequency-based methods falter in challenging conditions, SampEn and MSE effectively detect target echoes. Notably, MSE maintains detection capabilities even when the Doppler shift is negligible and the SRR drops to 0 dB. These findings highlight the robustness of entropy-based methods in complex underwater acoustic environments, suggesting their potential for enhancing real-time sonar systems and underwater surveillance applications.

Mao et al. [31] introduces an innovative approach for detecting shortwave defects in railway tracks by analyzing axle box acceleration signals. The authors propose a new metric called Dispersion Transition Entropy (DTE), which quantifies the dynamic complexity of time series data by examining transitions between dispersion patterns. To enhance the sensitivity of this measure, they integrate the Jensen–Fisher Divergence (JFD), a statistical tool adept at highlighting local differences in probability distributions. By computing the JFD between dispersion-transition distributions of consecutive sliding windows, the method effectively identifies anomalies such as rail corrugation and impact defects. Experimental results demonstrate that this combined approach outperforms traditional methods in distinguishing chaotic signals from stochastic noise, offering a robust solution for real-time rail defect detection and contributing to improved railway maintenance and safety.

An innovative entropy-based metric designed to quantify synchrony in complex time series data was proposed by Lin A. and Lin G. [28]. The method extends traditional diversity entropy by incorporating a multiscale framework, enabling the analysis of signal complexity across various temporal resolutions. By evaluating the diversity of patterns within time series at multiple scales, the approach captures both local and global synchrony features, making it particularly effective for detecting subtle synchronization phenomena in nonlinear and nonstationary signals. The study demonstrates the utility of this metric through applications to both synthetic and real-world datasets, highlighting its robustness and sensitivity in identifying synchrony patterns that may be overlooked by conventional methods. The findings suggest that multiscale modified diversity entropy offers a valuable tool for researchers and practitioners in fields such as neuroscience, physiology, and engineering, where understanding the synchrony of complex systems is crucial.

A novel approach based on Fuzzy Diversity Entropy (FDE) to enhance the accuracy and sensitivity of fault detection in rotating machinery was introduced by Jiao et al. [17]. This method builds on traditional Diversity Entropy (DE) by addressing its limitations in detecting subtle signal variations caused by rigid classification boundaries. By integrating fuzzy set theory, FDE replaces fixed probability assignments with fuzzy membership degrees, enabling a more nuanced quantification of signal complexity and better preservation of diversity information. This enhancement allows FDE to effectively distinguish between similar cosine similarity values that DE might treat as equivalent, thus increasing sensitivity to minor signal changes. The effectiveness of FDE was validated using both simulated and experimental vibration signals from rotating machinery. Comparative analyses show that FDE outperforms conventional DE, Fuzzy Entropy (FE), and Permutation Entropy (PE) in terms of complexity quantification, parameter sensitivity, and computational efficiency. These results suggest that FDE is a robust and efficient tool for intelligent fault diagnosis, with strong potential for real-time monitoring and predictive maintenance of rotating machinery systems.

A novel signal processing framework to enhance the sensitivity and accuracy of quartz-enhanced photoacoustic spectroscopy (QEPAS) systems for gas detection was proposed by Zhang et al. [64]. The method combines Improved Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (ICEEMDAN), Permutation Entropy (PE), and Wavelet Threshold Denoising (WTD) to efficiently extract and denoise key components from complex acoustic signals. By decomposing the signal into intrinsic mode functions (IMFs) with ICEEMDAN, selecting relevant components using PE, and applying WTD to reduce residual noise, the approach significantly boosts the signal-to-noise ratio. Experimental validation shows that this integrated technique outperforms conventional denoising methods, resulting in more accurate gas concentration measurements. The work highlights the potential of advanced entropy-based and multi-stage denoising strategies in improving the performance and reliability of QEPAS systems for applications such as environmental monitoring, industrial safety, and medical diagnostics.

Wang et al. [59] introduces a novel entropy-based approach aimed at enhancing the accuracy of fault detection in rolling bearings. This method, termed Distance Similarity Entropy (DSE), integrates distance metrics with entropy calculations to effectively capture subtle nonlinear characteristics in vibration signals. By quantifying the similarity between signal segments through distance measures and assessing their complexity via entropy, DSE provides a more sensitive feature extraction technique compared to traditional entropy methods. Experimental validations demonstrate that DSE outperforms existing approaches in identifying bearing faults, especially in scenarios with limited or noisy data, highlighting its potential for practical applications in machinery fault diagnosis.

Fan and Ding [15] presents a novel class of three-dimensional discrete memristive chaotic maps (3DDMCM) derived from a discrete cosine memristor model. These maps exhibit unique dynamic behaviors, including the generation of multi-type hidden attractors such as multi-wave, multicavity, multi-firework, and multi-diamond patterns, even in the absence of equilibrium points. By adjusting control parameters μ and b, the system can produce various chaotic attractors, demonstrating phenomena akin to multi-scroll patterns. Dynamic analyses reveal that the system possesses two positive Lyapunov exponents, high complexity, offset boosting, and diverse geometric control behaviors. A pseudo-random number generator (PRNG) based on this system was constructed, showcasing desirable statistical properties suitable for secure communication applications. Furthermore, the feasibility of implementing the 3DDMCM was confirmed through deployment on a DSP development board, underscoring its potential for practical engineering applications

Chapter 3

The Research Project

In this chapter, we outline the main ideas and objectives of this research project. Section 3.1 discusses entropy and complexity analysis in time series, highlighting its advantages an d limitations. Section 3.2 examines the advantages and limitations of the Bandt and Pompe method. Section 3.3 provides background knowledge on the entropy-complexity plane. Section 3.4 explores the entropy-complexity plane for a broad class of time series. Section 3.5 provides the asymptotic distribution of the entropy. Finally, the chapter concludes with the objectives of the research project and a case study related to our work.

3.1 Entropy and Complexity Analysis in Time Series: Advantages and Limitations

Entropy and complexity analysis in time series provides powerful tools for measuring the unpredictability and structural richness of dynamical systems, which means the systems that evolve in time. These methods help describe the behavior of a system using mathematical models. Entropy measures, such as Shannon entropy (which quantifies the uncertainty in a probability distribution) and permutation entropy (which measures the complexity of the order structure in time series using ordinal patterns), are used to quantify the degree of randomness or disorder in data. The major difference between Shannon entropy and permutation entropy is that permutation entropy is the Shannon entropy computed from the ordinal patterns (permutations) extracted from a time series. The complexity measures assess the balance between order and chaos. Entropy and complexity measures are powerful tools for identifying nonlinear patterns in time series data, and together, they are particularly valuable for distinguishing between deterministic and stochastic behavior by revealing hidden structures and irregular dynamics that traditional linear methods often overlook. While entropy and complexity analysis offers powerful insights into nonlinearity and chaos, capturing patterns that traditional linear methods often miss, it requires careful preprocessing, precise parameter tuning, and a solid understanding of the system's domain to avoid misleading conclusions. Non-linearity refers to relationships within the data where small changes in input can lead to disproportionately large or unpredictable changes in output, often seen in complex real-world systems such as biological signals or financial markets. Choosing the right parameters, such as embedding dimension and time delay, is crucial for accurately capturing the underlying dynamics, and without domain knowledge, interpreting the results and identifying meaningful patterns can be challenging. Despite these limitations, entropy and complexity remain essential in modern time series analysis for uncovering hidden dynamics beyond the reach of traditional linear methods. Linear methods, such as auto-correlation, linear regression, and Fourier analysis, assume that relationships within data are proportional and predictable, often focusing on averaged behavior, periodicity, or stationary patterns. However, many real-world systems (like the brain, heart, or climate) display nonlinear behavior, where the output does not change in a simple, direct way with the input. Entropy and complexity measures are specifically designed to capture these irregularities, revealing subtle structures, transient changes, or chaotic patterns that linear tools often overlook or misinterpret. This makes them invaluable for exploring complex, dynamic, and nonlinear systems where traditional approaches fall short.

3.2 The Bandt and Pompe Method: A Robust Approach

The concept of ordinal patterns in time series can be effectively studied through real world examples. Traditionally, numerous algorithms, techniques, and heuristics have been employed to estimate complexity measures from real world data.

However, these methods often perform well only for low-dimensional dynamical systems and struggle when noise is introduced. Low-dimensional dynamical systems are systems whose behavior can be described using a small number of variables or equations, typically two or three, such as the logistic map, or pendulum. These systems exhibit rich and often chaotic dynamics but remain mathematically tractable and easier to analyze using entropy and complexity measures. Because of their limited dimensionality, the patterns within the data are more distinct, making it easier to extract meaningful information.

The Bandt and Pompe method overcomes this limitation by providing a robust approach that remains reliable even in noisy environments. In time series analysis, key complexity parameters such as entropy, fractal dimension, and Lyapunov exponents play a crucial role in comparing neighboring values and uncovering the underlying structure and dynamics of the data. A Lyapunov exponent measures the average rate at which nearby trajectories in a dynamical system diverge or converge. It provides deeper understanding of system's behavior.

The advantages of Bandt & Pompe methods:

- Simplicity

- Extremely fast calculation
- Robustness
- Invariance to nonlinear monotonous transformations

This method exhibits low sensitivity to noise and naturally accounts for the causal order of elements in a time series. As a result, it can be applied to various real-world problems, particularly in differentiating between chaotic and stochastic signals.

Despite its limitations, researchers have developed extensions to the original method to address its shortcomings and enhance its applicability to a broader range of complex systems.

3.3 Statistical Complexity measures

Bandt and Pompe introduced a highly effective method for analyzing time series within this framework. They calculated Shannon entropy based on the histogram of causal patterns and successfully identified chaotic components in sequences of words, among other applications.

Later, Rosso et al. [47] expanded this analysis by introducing an additional dimension: the statistical complexity derived from the same histogram of causal patterns. The authors have contributed to a wide range of applications. This approach, which utilizes the entropy-complexity plane, has been successfully applied to the visualization and characterization of different dynamical regimes as system parameters change [4, 9, 12, 18, 19, 48, 67, 68], as well as to optical chaos [29, 54, 56, 62, 66], hydrology [21, 52, 55], geophysics [11, 50, 53], engineering [2, 3, 41, 61], biometrics [49], characterization of pseudo-random number generators [13, 14], biomedical signal analysis [22, 24, 25, 27, 33, 34, 35, 36, 37, 38, 39, 40, 63],and econophysics [6, 7, 8, 63, 65, 69, 70], to name a few.

After computing all symbols as described in Chapter 1, the histogram proportions are used to estimate the probability distribution of ordinal patterns. From this distribution, two key descriptors are calculated to characterize the time series:

1. Entropy
2. Statistical complexity

The most common metric for the first descriptor is the normalized Shannon entropy, defined as:

$$H(\mathbf{p}) = -\frac{1}{\log k} \sum_{\ell=1}^{k} p_\ell \ln p_\ell. \tag{3.1}$$

Here, $k = D!$ represents the total number of possible permutation patterns. This entropy is bounded within the unit interval:

- It reaches its minimum value $(H = 0)$ when a single pattern dominates for some $p_\ell = 1$ for some ℓ
- It achieves its maximum $(H = 1)$ under uniform probability $p_\ell = 1/k$ for all ℓ.

This normalized entropy is often termed permutation entropy in time series analysis.

While normalized Shannon entropy is a powerful tool for quantifying disorder, it fails to fully characterize complex dynamics. To address this limitation, López-Ruiz et al. [30] introduced the disequilibrium Q concept, which quantifies the deviation of a probability distribution $\mathbf{p}$ from a uniform (non-informative) equilibrium state. López-Ruiz and the team employed the Euclidean distance between $\mathbf{p}$ and the uniform distribution, providing a complementary metric to Shannon entropy for assessing structural complexity in systems.

The Jensen-Shannon distance between histogram of proportion $\mathbf{p}$ and the uniform probability function $\mathbf{u} = (1/k, 1/k, \ldots, 1/k)$, where $k = D!$ corresponds to the number of possible permutation patterns provides a robust metric for quantifying deviations from uniformity. This distance measure, derived from the symmetric Jensen-Shannon divergence, is particularly suited for analyzing ordinal pattern distributions due to its ability to capture both structural differences and statistical equilibrium in time series data. It is defined as:

$$Q'(\mathbf{p}, \mathbf{u}) = \sum_{\ell=1}^{k} p_\ell \log \frac{p_\ell}{u_\ell} + u_\ell \log \frac{u_\ell}{p_\ell}. \tag{3.2}$$

Lamberti et al. [20] proposed Jensen-Shannon distance as a symmetric metric rooted in the Jensen-Shannon divergence. As the reference model, most works consider the uniform distribution $\mathbf{u} = (1/k, 1/k, \ldots, 1/k)$. The normalized disequilibrium is defined as follows

$$Q = \frac{Q'}{\max\left(Q'\right)}, \tag{3.3}$$

where $\max(Q')$ is defined as follows

$$\max(Q') = -2\left[\frac{k+1}{k}\log(k+1) - 2\log(2k) + \log k\right]. \tag{3.4}$$

With this, Lamberti et al. [20] proposed complexity as a measure of the statistical complexity of the underlying dynamics, which is defined as

$$C = HQ, \tag{3.5}$$

where both H and Q are normalized quantities, therefore C is also normalized.

3.4 The Entropy Complexity Plane

The entropy-complexity plane is a two-dimensional representation where time series are mapped based on their entropy and statistical complexity. These metrics are derived from ordinal pattern distributions obtained through embedding dimension D that are mapped on histograms of $D!$ bins.

3.4.1 Key Dynamics in the plane

1. Highly Ordered Systems, where the behavior is very predictable, structured, and often repeats in a regular pattern over time.

   Example: Strictly monotonic time series.

   - Produces a single ordinal pattern ($H = 0$).
   - Maximal disequilibrium (distance from uniform distribution).
   - Maps to $(0, 0)$, indicating minimal complexity.

2. Perfectly Random Systems

   Example: White noise

   - Uniform ordinal pattern distribution ($H = 1$).
   - Disequilibrium vanishes (distance $= 0$).
   - Maps to $(1, 0)$, reflecting maximal entropy without structural complexity.

The two extreme values are proved by Anteneodo & Plastino [1]. Expressions for the boundaries, derived using geometrical arguments within space configurations, were proposed by Martin et al. [32]. These formulations provide a structured approach to understanding and analyzing the spatial behavior of specific systems or models. The lower boundary is characterized by a smooth curve, whereas the upper boundary consists of $D! - 1$ distinct segments. As the embedding dimension D approaches infinity, the upper boundary gradually converges into a smooth curve. Example for the entropy complexity plane is shown in Figure 3.1

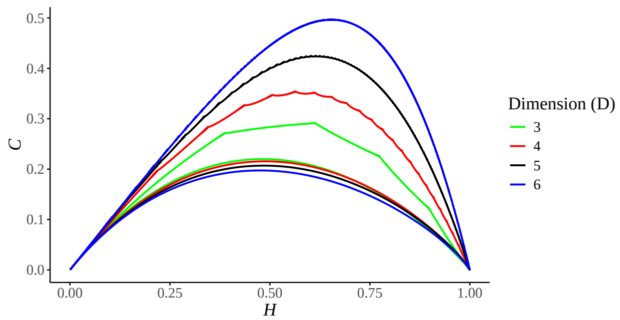

Figure 3.1: Entropy Complexity Plane for Embedding dimension 3, 4,5, and 6

3.5 Asymptotic Distribution of the Shannon Entropy under the Multinomial Model

The Multinomial distribution describes how observations fall into categories when an adequate model is available. It is similar to the Multivariate normal distribution, which is one of the continuous Multivariate distributions. Furthermore, it has received considerable attention from researchers, both in theoretical studies and in applications related to discrete Multivariate distributions. The normalized Shannon entropy, often employed in applications like permutation entropy, can be rigorously connected to its asymptotic distribution through the lens of statistical estimation theory. When estimating entropy from finite data, the plug-in estimator (computed directly from observed frequencies) converges to a normal distribution as the sample size $N \longrightarrow \infty$ even for dependent processes such as Markov chains. The Statistical properties of entropy measures under Multinomial distributions are crucial for analyzing complex systems where entropy serves as a key descriptors. Rey at al [45] investigate the asymptotic distributions of various entropy measures specifically, the Rényi and Tsallis entropies of order q, as well as Fisher information when these are computed using maximum likelihood estimators of probabilities from Multinomial random samples. The authors demonstrate that the Tsallis entropy and Fisher information asymptotically follow a normal distribution, whereas the Rényi entropy does not exhibit asymptotic normality. Through simulation studies, the paper validates that these asymptotic models effectively describe a variety of data scenarios. Additionally, the study introduces test statistics for comparing different types of entropies derived from two samples, even when the samples have differing numbers of categories. An application of these tests to social survey data indicates that the results are consistent and offer a more general approach compared to traditional chi-squared tests.

In a subsequent study, Rey et al [43] focus on the statistical complexity measure defined as the product of normalized Shannon entropy and the Normalized Jensen-Shannon divergence between a given probability distribution and the uniform distribution. They derive the asymptotic distribution of this complexity measure under the assumption that the observed data follow a Multinomial distribution. Further the study demonstrates that, as the sample size increases, the distribution of the statistical complexity converges to a normal distribution, with its variance and bias determined by the dynamics of the underlying system. This result provides a theoretical foundation for using statistical complexity as a tool for analyzing systems where the probability distributions are estimated from finite samples. The results are validated with theoretical findings through numerical experiments, showing that the asymptotic normality holds even in scenarios where the Multinomial model is not strictly applicable, such as in applications involving Bandt and Pompe ordinal patterns.

Crucially, the convergence rate and limiting distribution depend on the system's correlation structure, which deviates from the standard Multinomial case. However, they remain tractable through spectral analysis, which involves examining the eigenvalues and eigenvectors of the transition matrix or the distributions of ordinal patterns [10, 46]. This connection underscores the reliability of normalized entropy measures in large data regimes while highlighting the need to account for dependence structures in finite sample applications.

Imagine a sequence of n independent trials, each resulting in precisely one outcome from a set of k distinct possibilities labeled $\pi^1, \pi^2, \ldots, \pi^k$ and so on. These outcomes are mutually exclusive, meaning only one can occur per trial, with respective probabilities $\boldsymbol{p} = \{p_1, p_2, \ldots, p_k\}$, such that $p_\ell \geq 0$ and $\sum_{\ell=1}^k p_\ell = 1$. The random vector $\boldsymbol{N} = (N_1, N_2, \ldots, N_k)$ counts the number of occurrences of the events $\pi^1, \pi^2, \ldots, \pi^k$ in the n trials, with $N_\ell \geq 0$ and $\sum_{\ell=1}^k N_\ell = n$. A $\boldsymbol{n}$ is a sample from $\boldsymbol{N}$ and it has a $k-$variate vector of integer values $\boldsymbol{n} = (n_1, n_2, \ldots, n_k)$. Then the joint distribution of $\boldsymbol{N}$ is

$$Pr(\boldsymbol{N} = \boldsymbol{n}) = Pr(N_1 = n_1, N_2 = n_2, \ldots, N_k = n_k) = n! \prod_{\ell=1}^{k} \frac{{p_\ell}^{n_\ell}}{n_\ell!}. \tag{3.6}$$

This situation is denoted as $\boldsymbol{N} \sim$ Mult$(n, \boldsymbol{p})$. [45]

In practical applications, the true probability distribution $\boldsymbol{p}$ governing a Multinomial system is typically unknown. Instead, estimators $\widehat{p_l}$, are derived empirically by calculating the observed frequency of each event π^l within the set of k possible outcomes $\boldsymbol{\pi} = \pi^1, \pi^2, \ldots, \pi^k$ across n independent trials. These frequencies approximate the underlying probabilities, enabling inference about the system's behavior. This maximum likelihood estimator (MLE) aligns with the empirical estimator derived from first-moment matching of the distribution. Due to its consistency, asymptotic normality, and computational tractability under regularity conditions, it remains the predominant choice in applied statistical modeling.

Shannon entropy quantifies the level of disorder within a system. When the system's behavior is entirely predictable, the Shannon entropy reaches its minimum, indicating complete knowledge of future observations. Conversely, when the system follows a uniform distribution where all possible outcomes have equal probability—the entropy is maximized, reflecting minimal knowledge about the system's behavior. Chagas et al. [10] have analyzed the asymptotic distribution of Shannon entropy in their study.

Moreover, other types of descriptors, such as Rényi entropy[42], Tsallis entropy[58], and Fisher information [16], have been proposed to extract additional information that is not captured by Shannon entropy. From these entropy measures, Fisher information has garnered more attention due to its unique properties. Fisher information is defined as the average logarithmic derivative of a continuous probability density function.

For discrete probability distributions, Fisher information can be approximated by calculating the differences between probabilities of consecutive distribution elements. A key distinction between Shannon entropy and Fisher information lies in their focus: Shannon entropy quantifies the overall unpredictability of a system, while Fisher information measures the rate of change between consecutive observations, making it more sensitive to small changes and perturbations.

The following equations define Tsallis entropy ($H_T^q(\widehat{\boldsymbol{p}})$), Rényi entropy ($H_R^q(\widehat{\boldsymbol{p}})$), and Fisher information measures ($H_F(\widehat{\boldsymbol{p}})$) [51] :

$$H_T^q(\widehat{\boldsymbol{p}}) = \sum_{\ell=1}^{k} \frac{\widehat{p_\ell} - \widehat{p_\ell}^q}{q-1}, \tag{3.7}$$

where the index $q \in \mathbb{R}\backslash\{1\}$

$$H_R^q(\widehat{\boldsymbol{p}}) = \frac{1}{1-q} \log \sum_{\ell=1}^{k} \widehat{p_\ell}^q, \tag{3.8}$$

where the index $q \in \mathbb{R}^+\backslash\{1\}$

$$H_F(\widehat{\boldsymbol{p}}) = F_0 \sum_{\ell=1}^{k-1} (\sqrt{\widehat{p}_{\ell+1}} - \sqrt{\widehat{p_\ell}})^2, \tag{3.9}$$

where the re-normalization coefficient is $F_0 = 4$ [51]

Rey et al. [45] investigated the asymptotic distribution of several entropy measures, including Shannon, Tsallis, Rényi entropy, and Fisher information, and provided the following formulation:

Let $\boldsymbol{Z} \sim N(\boldsymbol{\mu}, \sum)$, be a $k-$dimensional multivariate normal distribution with mean vector $\mu \in \mathbb{R}^k$ and covariance matrix $\sum = (\sigma_{\ell j})$. Then, for any

$\boldsymbol{a} \in \mathbb{R}^k$, the linear combination $W = \boldsymbol{a}^T\boldsymbol{Z}$, is normally distributed as:

$$W \sim N(\boldsymbol{a}^T\boldsymbol{\mu}, \sum_{\ell=1}^{k} a_\ell^2 \sigma_{\ell\ell} + 2\sum_{j=1}^{k-1}\sum_{\ell=j+1}^{k} a_\ell a_j \sigma_{\ell j}). \tag{3.10}$$

The estimated Shannon entropy is defined as:

$$H_s(\widehat{\boldsymbol{p}}) = -\sum_{\ell=1}^{k} \widehat{p_\ell} \log \widehat{p_\ell}. \tag{3.11}$$

The asymptotic variance $\widehat{\sigma}^2$ of the entropy estimator is given by:

$$\widehat{\sigma}^2 = \frac{1}{n}\sum_{\ell=1}^{k} p_\ell(1-p_\ell)(\log p_\ell + 1)^2 - \frac{2}{n}\sum_{j=1}^{k-1}\sum_{\ell=j+1}^{k} p_\ell p_j (\log p_\ell + 1)(\log p_j + 1). \tag{3.12}$$

These formulas serve as the basis for the subsequent case study in our research.

3.6 Case Study of Asymptotic Distribution of the Complexity

Statistical complexity is defined as the product of two normalized quantities:

- The Shannon entropy
- The Jensen-Shannon distance between the observed probability distribution and the uniform distribution

In this section we discuss three key aspects with real world scenario:

1. **Significance of Asymptotic Complexity Distributions**: Why understanding large-sample behavior matters for statistical inference
2. **Multinomial Model Framework**: Derivation of the asymptotic distribution for statistical complexity under Multinomial assumptions

3. **Practical Formula**: A working equation for calculating the asymptotic distribution of complexity

As a case study for our work, we consider data from the Bearing Data Center and the seeded fault test data from Case Western Reserve University, School of Engineering. The datasets includes ball bearing test data for normal bearings as well as single-point defects on the fan end and drive end. Data were collected at a rate of $48,000(48k$ drive-end) data points per second during bearing tests. Each file contains motor loads $(0, 1, 2,$ and $3)$, drive-end vibration data, and fan-end vibration data. The approximate motor speeds in RPM during testing: $1797, 1772, 1750,$ and 1730. For our case study, we consider two time series (Normal Baseline and $48k$ Drive-End) with a motor load of 0 and an RPM of 1797.

The primary objective of this study is to detect malfunctioning machinery by analyzing two time series using ordinal patterns. We introduce a distance metric based on the ordinal structure of the segments to quantify similarity. This metric facilitates the identification of faulty machines across various embedding dimensions, ranging from 3 to 6. For this case study, we employ an embedding dimension of 3 for convenience; subsequent analyses will extend to the remaining dimensions to compare results. Permutation entropy under asymptotic conditions is computed by considering the probability distribution of ordinal patterns. The results are further analyzed using the complexity–entropy plane, providing insights into the system's dynamics.

Initially, we analyzed the complete datasets from two time series such as one comprising $250,000$ data points representing the normal baseline at motor load 0, and another containing $2,540,000$ data points from the $48k$ drive end under the same motor load. We computed entropy and complexity measures fro these entire datasets, with the results presented in the Table 3.1

Entropy	Complexity	Std Deviation	Semi Length
0.665235	0.226447	0.358893	0.000441
0.772973	0.170954	0.324376	0.001287

Table 3.1: Entropy Complexity Results

Subsequently, we segmented the data into batches of $10,000$ points, categorizing them as either 'Normal' or '48k Drive End'. We then performed a batch wise comparison of entropy and complexity metrics to identify fault data segments. The normal dataset comprises 25 batches, all corresponding to motor load 0, while the $48k$ drive end dataset includes 254 batches. Due to the extensive volume of entropy and complexity data generated, the complete results table is not included in this report. However, the entropy–complexity plane effectively illustrates both batch-wise and full-data analyses. As depicted in Figure 3.2 below, faulty machines form a distinct cluster in the entropy–complexity plane, highlighting their deviation from normal operational patterns. It is clear from the graph that there are both overlapping and non-overlapping confidence intervals. This indicates that some machines differ significantly, while others do not. The main purpose of our experiment is to identify faulty machines. Therefore, we highly recommend extending these results by increasing the embedding dimension to better understand the final outcomes. The general framework of this experiment is also provided in this chapter to clarify the main objective of the research.

The general framework for analyzing entropy-complexity planes with confidence intervals are given as follows.

1. **Calculate Entropy (H) and Complexity (C):** appropriate estimator are Shannon entropy, statistical complexity measures
2. **Compute Confidence Intervals:** Generate multiple resampled datasets to estimate the variance of H and C.

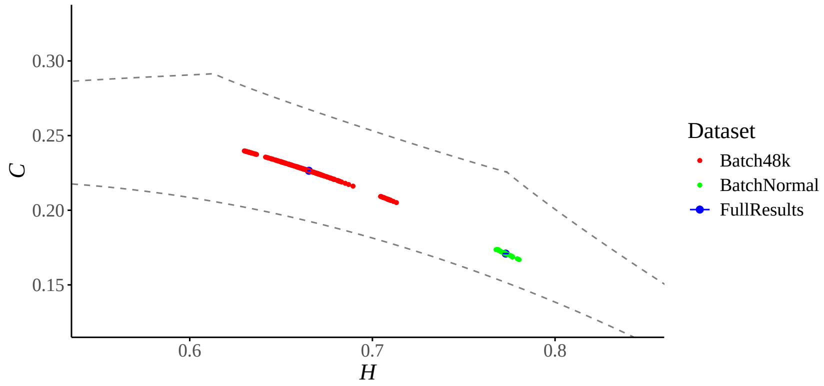

Figure 3.2: Entropy Complexity Plane

3. **Plot on Entropy-Complexity Plane:**
    - Axes:x-axis: Entropy (H), y-axis: Statistical complexity (C)
    - Data Points: Plot individual or aggregated results.
    - Confidence Regions: Represent uncertainty
4. **Interpretation**

Region of Plane	Interpretation
High H and High C	Complex, structured systems
Low H and Low C	Simple, predictable systems
High H and Low C	Random/noisy systems
Low H and High C	Non-random systems

5. **Statistical testing:**
    - Compare confidence intervals between groups to assess significant differences.
    - Overlapping intervals $\rightarrow$ No significant difference.
    - Non-overlapping intervals $\rightarrow$ Potential significance.

Chapter 4

Future Works

As a short summary, we have completed the necessary preliminaries studies on various topics such as:

- Entropy
- Complexity
- Entropy Complexity Plane
- Confidence interval
- Multinomial distribution.

Also we have examined the relevant research articles by Bandt & Pompe [5], and statistical properties of the entropy from ordinal patterns, asymptotic distribution of certain types of entropy under the Multinomial law, and the asymptotic distribution of the permutation entropy studied by Rey et.al [43, 44, 45].

This proposal has three objectives in order to continue this research work.

- Define a data base of time series for clustering, i.e., finding similar time series.

- Extract all the features we know from their Bandt & Pompe symbolization (Shannon, Tsallis and Renyi entropies, Fisher information measure, complexities, and the available confidence intervals)
- Use those features for time series clustering

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