Lab4

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1 Data modelling

2 Modeling the Experimental Part

In this section, we discuss the modeling of the experimental part, focusing on key aspects such as the choice of data, selection of experiments, validation procedures, and methods for comparing results.

2.1 Data Selection

The data utilized in this paper comprises historical data for SPX (S&P 500), spanning from the year 1927 to November 2023. The data is collected on a daily basis and sourced from Yahoo Finance. Specifically, the algorithm is applied using the daily closing prices, which have been prefiltered to exclusively include this closing price data. It's noteworthy that the algorithm demonstrated in this paper is versatile and can be applied to any stock or index.

2.2 Experiments and Validation

The experiments conducted involved the analysis of daily data from the S&P 500 and other prominent indexes. Validation procedures were executed by predicting the price for the subsequent day based on a subset of these indexes and subsequently comparing the predictions with the actual results. Notably, the accuracy of the tests ranged between 52% and 57%, surpassing the probability of a mere coin flip. This outcome suggests a small but noteworthy performance, warranting careful consideration in future applications.

2.3 Advantages Over Existing Approaches

When comparing our approach to existing methodologies, distinct advantages emerge. In the current landscape, prevalent strategies for entropy calculation often hinge on the entire dataset, giving precedence to recent prices with augmented probabilities. In contrast, our approach introduces a fundamental shift in perspective.

In our methodology, every individual price point is afforded the same probability weight. This deliberate departure from assigning varying probabilities based on recency fundamentally alters the conventional linearity considerations associated with price sequences. Rather than treating prices as a linear progression, our approach emphasizes their collective nature as a set.

By eschewing the conventional weighting schemes favoring recent prices, our model captures a more egalitarian representation of the entire dataset. This not only introduces a nuanced understanding of the price dynamics but also opens avenues for uncovering patterns and insights that may be overshadowed by approaches emphasizing recent trends.

This nuanced handling of probabilities and a departure from the linearity-centric mindset contribute to the distinctive strengths of our approach, presenting a compelling case for its adoption in the realm of entropy-based stock analyses.

2.4 Mathematical Models

The algorithm underpinning this study draws inspiration from Sinai entropy [11], employing entropy calculations in two distinctive ways, each contributing to a nuanced understanding of price dynamics.

1. $h(T) = \sup_{\xi} h(T, \xi)$: This expression represents the supremum of entropy over all possible partitions, encapsulating the highest achievable entropy value within the system.

2.

$$h(T,\xi) = -\lim_{n\to\infty} \frac{1}{n} \sum_{i_1,\ldots,i_n} \mu(T^{-1}C_{i_1} \cap \ldots \cap T^{-n}C_{i_n}) \log \mu(T^{-1}C_{i_1} \cap \ldots \cap T^{-n}C_{i_n}).$$

The entropy theorem posits the equality of these two formulas when ξ serves as a generating partition. Consequently, the algorithm assesses market dynamics by evaluating whether prices are likely to ascend or descend, emphasizing the significance of a generating partition in this determination.

Recognizing the potential limitations in representing the limit exactly, the algorithm introduces a pragmatic approach. Instead of relying on a singular value, the mean average of six values from the entropy subset is considered. A pivotal decision is then made: if the square of the supremum exceeds the mean entropy subset value, it signifies a probable increase in the price.

This intricate interplay of mathematical formulations and practical considerations underscores the algorithm's sophistication in forecasting price movements and contributes to its robust analytical capabilities.

3 Case Study

3.1 Implementation

4 Related work

5 Citations

[1] [11] [6] [5] [3]
[12] [9] [14] [13] [4]
[10] [7] [15] [2] [8]

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