Point estimate model

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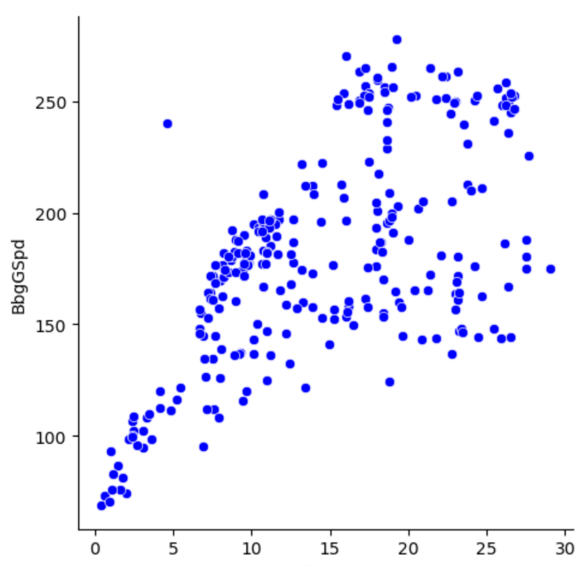
In this study, a new mathematical model of bond trading is presented, which differs from existing algorithms that focus on time series of numerical characteristics of the trading process. They deal with a fixed number of features and their prediction, without discussing the entire process. Instead of these approaches, a model of the trading process itself is being proposed. The idea can be briefly explained as follows. On a fixed day for a fixed company, all trading events can be considered as points in a rectangular spread. These points are sensible to be random, depending on each other and on points from the previous day. In model, the points for the following days are being attempted to be predicted, effectively taking into account the current points in the most correlated positions. Accordingly, the model was constructed in several steps. Initially, the "neighbors" concept was discussed. The second step is devoted to the approximation of the conditional probability of the appearance of a point on the next day. Here, various approaches are being proposed that work effectively for different companies and varying numbers of neighbors. In the next step, the forecasting ability of the model is being introduced. Thus, the work will comprise three parts, accompanied by prediction images and simulations.

Model represents all trades involving selected bonds as points in a two-dimensional coordinate system, with the horizontal axis representing the tenor and the vertical axis representing BbgGSpd. Specifically, the picture below illustrates all the bonds traded by The Goldman Sachs Group, Inc.



Goldman Sachs Group.png

Figure 1: Points corresponding to bonds trades for 2014-12-19 The Goldman Sachs Group, Inc.

- **Tenor** is the year fraction from current date and the date when the bond is expected to mature or be called away by the issuer.

- **BbgGSpd** The G-spread value obtained from Bloomberg is a measure of the credit risk premium of an individual bond issue.

We can calculate the probability of a bond appearing on the next day using the following formula:

$$\varepsilon_0^n \cdot \alpha + \varepsilon_1^n \cdot \beta_1 + (\varepsilon_1^n)^2 \cdot \beta_2 + \varepsilon_2^n \cdot \beta_3 + (\varepsilon_2^n)^2 \cdot \beta_4 + \gamma = p_{n+1} \tag{1}$$

$$p_{n+1} = P\{\varepsilon_0^{n+1} = 1 | \varepsilon_0^n, \varepsilon_1^n, \varepsilon_2^n, \varepsilon_3^n\}$$

Where, p_{n+1} is conditional probability to have point in the square on the next day.

$\varepsilon_r^n = \sum\limits_{\text{occupied cells}} 1$ is the "rth circle of neighbors" refers to the neighboring circles that we believe have an influence on the central square, which we designate as ε_0^n.

Coefficients $\alpha, \beta_0, \beta_1, \beta_2, \beta_3, \gamma$ are found using least square method, minimizing

$$\sum_{k=0}^{S} (p_{n+1} - \hat{p}_{n+1,k})^2,$$

where:

$$p_{n+1} = P\{\varepsilon_0^{n+1} = 1 | \varepsilon_0^n = X_0, ..., \varepsilon_k^n = X_k\} \approx \frac{P\{\varepsilon_0^{n+1} = 1, \varepsilon_0^n = X_0, ..., \varepsilon_k^n = X_k\}}{P\{\varepsilon_0^n = X_0, ..., \varepsilon_k^n = X_k\}}$$

We calculate the probability based on the frequency of occurrences of combinations of the number of neighbors in our dataset.

$$\hat{p}_{n+1} = \varepsilon_0^n \cdot \alpha_0 + \varepsilon_1^n \cdot \beta_1 + (\varepsilon_1^n)^2 \cdot \beta_2 + \varepsilon_2^n \cdot \beta_3 + (\varepsilon_2^n)^2 \cdot \beta_4 + \gamma$$

By substituting the coefficients into the initial formula (1), we obtain the expected probability value of the bond appearing in the square on the next day $\hat{p}_{n+1}$. Whether a bond will appear in a particular square on the next day is dependent on whether a bond has been present in that square for all the days assigned for training and the number of neighboring squares within the "nearest" circles.

The Point estimate model follows an unconventional structure and utilizes hyperparameters like partitioning and the number of neighbors in training circles, which enables it to achieve quite accurate predictions. Nevertheless, it doesn't fit into the traditional classification or regression categories commonly used in classical machine learning.