

Wisdom of Crowds Algorithm for Stock Market Predictions

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Abstract. *In this paper we present a mathematical model for collaborative filtering implementation in stock market predictions. In popular literature collaborative filtering, also known as Wisdom of Crowds, assumes that group has a greater knowledge than the individual while each individual can improve groups performance by its specific information input. There are commercially available tools for collaborative stock market predictions and patent protected web-based software solutions. Mathematics that lies behind those algorithms is not disclosed in the literature, so the presented model and algorithmic implementation are the main contributions of this work.*

Keywords. Collaborative Filtering, Wisdom of Crowds, Crowdsourcing, Stock, Market, Prediction

1. Introduction

In 1906, during the West of England Fat Stock and Poultry Exhibition, Francis Galton discovered the mathematical and statistical patterns of group average estimations and their advantages over individual ones. At the event, a group of estimators successfully provided an average weight value of an ox remarkably close to the real value [3]. This phenomenon is a foundation of the group estimating systems that we call collaborative filtering (CF) systems.

CF systems, which are also known by the more marketable terms Wisdom of Crowds and Crowdsourcing, are implemented in various domains like systems for rating

books, movies, music and stocks [17].

Modern CF considerations origin from the early 90s of the 20th century [2] when the term CF was coined by Goldberg et al [4]. The basic assumption is that group of individuals can yield more knowledge than an individual alone while at the same time each individual can probably improve group's performance by contributing with its specific small chunks of knowledge.

One interesting CF application is a very popular stock rating system that is operational since 2006 and its predictive power is confirmed in literature [8]. The system is patent protected¹. Those patents cover various features while providing limited considerations about the algorithm that lies underneath the rating system. As it is stated on the project's website, the algorithm is kept secret and according to developers it is a subject of constant improvements, upgrades and fine tuning.

This paper presents a model designed to work in the similar fashion and to yield similar results, having in mind not to make a copy of the mentioned system. Existing system's help was used as a general guidance for developing the presented mathematical model.

2. Predicting Stock Markets

Stock Market forecasting is popular and attractive for both laymen and scientists. Besides widely used and economically confirmed fundamental analysis of the companies' performance, the challenge is to

¹US patent 7813986 and 7882006

create an artificial intelligence (AI) model that will predict trends and events. Due to that a wide range of techniques was adopted, tested and some interesting results were achieved. From technical analysis considerations, fuzzy logic [1], neural networks [16] to hybrid approaches [6]. Many of the presented models achieved positive results in a short term. Since stock market is subject of constant changes and various influences, it is a greater challenge to achieve performance in a long term.

There is a known logical problem that implementation of the prediction model, thus interference of the agents using the model, causes degradation in performance of the model itself since system behaviour is changed in a global perspective. It is known that algorithms used in automatic trading have a lifespan measured in weeks, both because of their solely influence on the market and their influence on each other when more algorithms work on the same market. Similar problems with possible impacts on the market, and not just on the model performance, are utilizations of the High frequency Trading Systems (HFT)². Following these considerations we can conclude that some form of feedback and system self-correction is needed to ensure long term model performance.

CF approach offers a solution to this problem in a form of constant monitoring and evaluation of all agents in the system and thus self-adapting the prediction system. This type of predictive model will be described in the following chapters.

3. Collaborative Filtering Approaches

CF systems are divided into two main categories, memory-based (or user based) and model-based (item-based) [14]. Former utilize the entire user-item database for

prediction. These systems find neighbours between clusters of user-item pairs. On the other hand model based systems develop a model for recommendation based on history of user ratings. Common problem in item based systems is a "cold start" issue where users must rate sufficient items to induce the system to make right predictions [15].

Group lens [7] suggested an automated CF model for personalized usenet messages and Pearson correlation was used to weight user similarity. An extension of the Group lens method was the use of Spearman rank correlation coefficient instead of Pearson correlation. Spearman correlation does not rely on model assumptions but correlates ranks instead of rating values. These memory based algorithms are the most widely implemented [12].

Popular commercial CF systems are Amazon [11] and Netflix. Amazon is an e-commerce company that introduced item-to-item based filtering, a proprietary algorithm that generates recommendations based on the similarity of items³. Amazon's approach was the reaction to, at that time, inefficient user based systems. Netflix is an on-demand streaming media which maintains a personalized video-recommendation system based on users' ratings and reviews. In 2006 the company launched a competition with a bounty of 1M dollars for a 10% improvement of their CF algorithm.

Some psychological centric works suggest that it is in human nature to estimate the boundaries of predictions [5], [13]. Griffins et. al conducted tests on everyday problems like estimating human life spans, where they found that individuals make very similar predictions to probabilistic models [5]. The most known pitfall in group relations is the groupthink phenomenon, where the group tries to minimize conflict making consensus decisions [10].

Groupthink also relates to user relations in CF systems because users' votes, reviews and thoughts can influence other users.

²International Organization of Securities Commissions (IOSCO) - Regulatory Issues Raised by the Impact of Technological Changes on Market Integrity and Efficiency

³US patent 6,226,649

4. Algorithm

4.1. Rating system

We define a set of stocks used in game $St = \{st_1, st_2, \dots, st_n\}$ where n is a number of stocks in a game. Stock price i.e. value is considered through time where t_0 is start time of interest, e.g. prediction insertion, and t_i is observed moment so $t_i = t_0 + \Delta t$ where Δt represents time passed. We define stock value at the starting time and at the observed time as V_{St_0} and V_{St_i} respectively. System gets its inputs from a set of players Pl , where each player pl enters predictions. Stock gain is defined as

$$\Delta St_i = \left(\frac{V_{St_i}}{V_{St_0}} \right) * 100 \quad (1)$$

In the same manner, we define index values as V_{It_0} and V_{It_i} for starting value and value at the observed moment and index gain is defined as

$$\Delta It_i = \left(\frac{V_{It_i}}{V_{It_0}} \right) * 100 \quad (2)$$

Each pick has an orientation o from a set O that can represent outperformance or underperformance of the stock compared to the selected index $O = \{1, 2\}$ respectively.

To achieve a one-line calculation for a prediction score we introduce two multipliers:

$$M_{\Delta S} = \begin{cases} 1, & o = 1; \\ -1, & o \neq 1 \end{cases} \quad (3)$$

$$M_{\Delta I} = \begin{cases} 1, & o = 1; \\ -1, & o \neq 1 \end{cases} \quad (4)$$

Score for the individual prediction is calculated as

$$\varsigma_{pr} = \Delta St_i * M_{\Delta S} + \Delta It_i * M_{\Delta I} \quad (5)$$

We define player's score as

$$\varsigma_{pr} = \sum \varsigma_{pr|pl}, t > t_{0+\Delta P} \quad (6)$$

where $t_{0+\Delta P}$ connotes moment of the pending period end for a particular stock prediction. Pending period is introduced to eliminate possible short-term manipulations.

To calculate accuracy for a given player we define a set of player's predictions $Pr = \{pr_1, pr_2, \dots, pr_n\}$. Each player has its own predictions Pr_i . Global predictions count of a given player is $|Pr|$ and positive predictions count $|Pr^+|$ is number of predictions in which player achieved positive score $Pr^+ \subseteq Pr$.

$$Pr^+ = \{pr : pr \in \{pr : \varsigma_{pr} > 0\}\} \quad (7)$$

In order to minimize computational requirements, we normalize each player's score to 100. To find player's prediction accuracy we need average number of predictions for all players N_{pl} :

$$N_{pl} = \frac{|Pr|}{|Pl|} \quad (8)$$

To calculate accuracies of all active players $A = \{\alpha_1, \alpha_2, \dots, \alpha_n\}$ we need mean accuracy \bar{A} for all players

$$\bar{A} = \frac{\sum_{i=1}^n \alpha_i}{N_{pl}} \quad (9)$$

Furthermore, we define normalized prediction count for each player as

$$|\widehat{Pr}_i| = \begin{cases} |Pr_i|, & |Pr_i| \leq 100; \\ 100, & |Pr_i| > 100. \end{cases} \quad (10)$$

and normalized positive pick count

$$|\widehat{Pr}^+| = \begin{cases} |\widehat{Pr}^+|, & |Pr_i| \leq 100; \\ |\widehat{Pr}_i|, & |Pr_i| > 100. \end{cases} \quad (11)$$

We have normalized positive predictions count for a player as

$$\widehat{Pr}^+ = \frac{100}{|Pr|} * |Pr^+| \quad (12)$$

Individual normalized accuracy for player i

is defined

$$\alpha_i = \frac{|\widehat{Pr}^+|}{|Pr|} * 100 \quad (13)$$

When aligned with other players' accuracies we get individual rating

$$R_T = |Pr| * \alpha_i \quad (14)$$

Using Bayesian average we can calculate accuracy rank i.e. probability of player's accuracy for those with less than 100 picks as

$$R_A = \frac{|\bar{Pr}| * \bar{A} + R_T}{|\bar{Pr}| + |Pr|} \quad (15)$$

To rank all players we consider their scores and accuracies jointly. First we calculate player's score rating as a percentile rank for player i . After sorting ascendantly, score and accuracy percentile ranks are defined:

$$y_{Si} = \frac{pl_i}{|S_{pl}|} * 100 \quad (16)$$

$$y_{Ai} = \frac{pl_i}{|A|} * 100 \quad (17)$$

Raw rating for each player is calculated as:

$$r_i = 2/3 * y_{Si} + 1/3 * y_{Ai} \quad (18)$$

and we have a sorted set of ranks $R = \{r_1, r_2, \dots, r_n\} : r_i < r_{i+1}$ for each player i . Due to analogy raw ranks percentiles are defined

$$y_{Ri} = \frac{pl_i}{|R|} * 100. \quad (19)$$

When we have calculated players' ratings, the next task is to calculate stock ratings accordingly. To ensure fraud resistance, we implement following minimal number of predictions $\min |Pr_{St_i}| = 5$, and at least one player must be among top 40% of all players $\min Y_{Ri} = 60$. Stocks that satisfy minimal conditions are denoted st'_i where $St' \subseteq St$. Therefore, we find players that made predictions for the given stock $Pl' \subseteq Pl$. Then we

apply the qualification algorithm

$$\exists St'_i \implies (|Pr_{St_i}| >_{\min} |Pr_{St_i}|) \wedge (\exists p_{Li} \implies (y_{Ri} >_{\min} Y_{Ri} = 60)). \quad (20)$$

Every qualified stock has at least one positive or one negative prediction among all its predictions $\forall st'_i \implies Y_{RO} \vee Y_{RU}$. Y_{RO} is defined as outperform prediction, while Y_{RU} are underperformed predictions. Taking into account players rating to rate the particular stocks we use the sum of stock predictions

$$\sum_{RATINGS} = \sum_i^{|RO|} y_{ROi} + \sum_i^{|RU|} y_{RUi} \quad (21)$$

thus stock score θ_i is

$$\theta_i = \frac{\sum_i^{|RO|} y_{ROi}}{\sum_{RATINGS}} \quad (22)$$

We calculate percentile ranks ordering stock scores $\Theta = \{\theta_1, \theta_2, \dots, \theta_p\} : \theta_i < \theta_{i+1}$ and percentile rank of a particular stock

$$y_{\Theta i} = \frac{i}{|\Theta|} * 100 \quad (23)$$

4.2. Keeping it fair

In order to prevent manipulation, besides delayed stock prices data, we have implemented several limitations to keep the prediction system fair. Limits include prediction maturity i.e. time span after a prediction starts affecting player's score, minimal number of active and mature predictions for a stock to have a rating, minimal rank for at least one player that entered his prediction for a stock to have a rating, number of active and mature predictions for a player to have a rank and finally minimal score that prediction with positive score must achieve to start counting for a player's overall score.

5. Evaluation

As it is mentioned earlier, one of the problems of CF systems is a cold start phenomenon. Same problem exists with our implementation. At the moment of writing of this paper, system is operational for more than six months with 47 active players. Total number of entered predictions was 667, half of them were active for 130 stocks.

Since both the elapsed period and players count are rather small, due to the system's cold start, no reliable statistical evaluation could be made. Here we give current gains of the top 10 stocks identified by the system just for illustration. Results are presented in Table 1. One possible criticism of the presented algorithm can be a possible occurrence of the groupthink phenomenon. Players that are not so experienced could imitate high ranked players and predict in the same way. The main concern is if the time component solely is enough insurance, since time-delayed imitating of the high ranked player can not yield the same result i.e. imitator will always stay one step behind. Also, if a high ranked player makes a mistake, negative score is cascading on the imitators too.

Table 1: Top 10 stocks by the system's rating compared to their yearly and monthly gain

Ticker	Rank	1 Y(%)	1 M(%)
VDKT-R-A	95.83	238.83	37.20
TISK-R-A	94.44	66.47	16.04
PBZ-R-A	93.06	10.22	3.00
LPLH-R-A	91.67	-51.68	-3.90
KODT-R-A	90.28	2.89	16.92
ISTT-R-A	88.89	-20.84	-6.58
HUPZ-R-A	87.50	16.83	11.88
CROS-P-A	86.11	66.24	3.17
VART-R-1	80.56	-32.08	20.62
SLRS-R-A	79.17	78.53	17.37

6. Future Work

6.1. Testing

Besides fine-tuning of the proposed algorithm, future work will cover measurement of the algorithms performance, identification of the groupthink problem and mitigation.

6.2. Fine Tuning

Based on the testing results, further improvements can be made on the algorithm. One of the most obvious fine tuning opportunities is an improvement of the final stock rating algorithm where individual player ratings are considered when calculating the stock score. As can be seen in formula (21) all players' ratings are taken as they are. Here a simple exponential or similar transformation can be used to increase the weight for higher ranked players.

6.3. Algorithmic Trading Considerations

Since the presented system implements feedback i.e. constant monitoring of each player's performance and correction of its influence on the stock rating, question is if it can be used to achieve positive trading results of an AI trader. Outperforming predictions from highly ranked players could be used as an indicators for buying and under performing predictions for short-selling. In that way positive results could hypothetically be achieved from both directions.

7. Conclusion

There is a probative evidence that CF can generate valuable knowledge from the groups of people about the specific topic. That kind of knowledge extraction mechanism found its use in various domains like entertainment where users can rate movies or music and more serious domains like education and business where users rate

books or stocks.

Stock rating systems exist on the market and their software implementations are described and protected by patents but mathematics and algorithms underneath are not publicly available. This paper describes one possible way of implementing CF idea for stock market predictions. The described implementation is very recent so quality assessment of the predictive model will be a subject of future research.

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