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A decision support system for stock investment recommendations using collective wisdom

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ABSTRACT

Previous research has shown that user-generated stock votes from online communities can be valuable for investment decisions. However, to support investors on a day-to-day basis, there is a need for an efficient support system to facilitate the use of the data and to transform crowd votes into actionable investment opportunities. We propose a decision support system (DSS) design that enables investors to include the crowd's recommendations in their investment decisions and use it to manage a portfolio. A prototype with two test scenarios shows the potential of the system as the portfolios recommended by the system clearly outperform the market benchmark and comparable public funds in the observation period in terms of absolute returns and with respect to the Reward-to-Variability-Ratio.

1. Introduction and motivation

The rise of user-generated content on the Internet enabled a wider public to participate in online content creation and publication without the need for deep technical expertise. The technical possibility to centrally aggregate the local contributions of a large crowd enables the creation of artifacts which are of equal or superior quality than those made by experts in the domain. Wikipedia, as an example, reaches a comparable quality to the renowned Britannica [19], solely depending on the contributions of a diverse anonymous crowd. This effect, coined as "wisdom of crowds" [41], is based on the diversity in information possession and processing of the individual members and is evident in a number of problem solving situations such as judging, estimating or decision making [18,28].

Estimation tasks are a problem class where group judgments prove to perform extraordinarily well. The reason behind is an effect called *bracketing* [39], which refers to the high likeliness that a part of the crowd will overestimate, while another part will underestimate the true value. Hence, averaging all judgments will lead to a more accurate judgment than that of the average judge [26]. Take an example: two people estimate the outside temperature for the next day as 60 °F and 80 °F, while the true temperature will be 73 °F. The estimates were wrong by 13 °F and 7 °F, or 10 °F on average. However, the mean of the two estimates, 60 °F and 80 °F, which is 70 °F, is off by only 3 °F. So using deviation as a measure, the average *judgment* outperforms the average *judge* [cf. 26].

One form of harnessing the crowd wisdom to improve decision making is the application of prediction markets. At prediction markets, participants can buy or sell contracts whose payoff is connected to a certain future event, e.g. "Candidate A will win the election". By dealing contracts over time, the contracts' prices reflect the market participants' collective judgment of the likeliness that the associated event will become true. The collective judgment has been proven to be quite close to the final result [3,18,40]. If designed appropriately, such prediction markets can be utilized to support decisions [7]. Preference markets are a closely related concept and have been used to apply the wisdom of crowd to evaluate emerging technologies at an early stage of product development [10,15]. The difficulty here is to prioritize resources for technologies who are most promising and which might emerge into product features. This problem is an instance of a typical investment problem and hence very close to the task in focus of this paper, the beneficial allocation of capital to capital market shares. Chen et al. [10] used a preference market to compare the crowd estimate of product feature ranking to a benchmark ranking done by an expert group and found indications that they reach comparable results if the preference market provides a sufficient (non-monetary) incentive. In the perspective of the financial domain, this finding suggests that trading strategies based on crowd recommendations might be able to perform as well as public funds managed by experienced domain experts even without a direct monetary reward for the crowd members. Specifically, virtual investing communities (VICs) (see Section 1.1) which collect user opinions on stock development usually provide non-monetary incentives for participation such as public reputation or access to exclusive information.

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Fig. 1. Example of VIC vote.

1.1. Wisdom of crowd in finance

With respect to the financial domain, there is extensive research on the value of user-generated content for stock investment decisions. Antweiler and Frank [2] analyze the information content of stock discussion boards and find evidence that message posts can be used to predict stock market trading volume and volatility and – to a small extent – stock returns. Mood analysis from Twitter messages can be used to improve prediction accuracy of the Dow Jones Industrial Average Index [8].

Stock discussion boards evolved into Internet portals, so called virtual investing communities (VICs), where members are able to provide their guess about a share's future performance in a structured way (see Fig. 1 for an example). Members can make a buy or sell recommendation for any share along with a target price at a specific future date (= *vote*). By doing so, the individual investors act like institutional analysts and the aggregation of the single votes of a share leads to a collective judgment of its prospects. Examples for such websites are CAPS[2] or sharewise.[3] As participants make very specific (price) predictions of a share, those platforms can be seen as a prediction market for share prices and are as such an enhancement of stock discussion boards with unstructured free-text information [4] that has to be preprocessed for analysis (including a certain loss of accuracy).

There is evidence in literature that information from these stock communities can be used to implement profitable stock investment strategies. Using data of the CAPS platform, Avery et al. (2011) find that stocks ranked highest by the community indeed show a better subsequent performance than those that were ranked low [4]. Especially short (i.e. sell) recommendations of the crowd are able to predict stock price declines. Further, they analyze the composition of the performance and find that the advantage of the crowd comes from stock selection rather than market timing or style/risk factors (as identified by Fama and French [17] and Carhart [9] which classify stocks by their market or risk profile).

An in-depth analysis of the CAPS data for investment purposes can be found at Hill and Ready-Campbell [22]. They find evidence, too, that a portfolio based on crowd voting is able to outperform the market index (S&P 500) and that the higher rated shares do indeed perform better. Specifically, they find that a crowd of about 250 people always outperforms the S&P 500 index. In addition, they rank the users according to their past performance and find that a selected group of experts from the crowd performs better than the whole crowd. They test several investment strategies for portfolio construction, but disregard transaction cost. While their analysis is comprehensive and their results are insightful, investors who want to make use of the effects for future scenarios are left with extensive analytical effort and not much guidance on how to transform results into actionable investment decisions.

Nofer and Hinz (2013) empirically show that the average institutional expert from the financial service industry and the average private crowd member are able to outperform the market. More surprisingly they also show that investors are on average significantly better off when trusting a crowd recommendation than following the advice of professional experts from banks. However, the authors do not provide and evaluate a system that implements their findings and which offers decision support for investors [34].

Making use of the value in crowd data for day-to-day investment decision is not a trivial task. Because analyses are complex (both in terms of method and data) and time-consuming when done manually, a decision support system proves to be helpful.

1.2. DSS for investment decisions

There is a vast amount of literature about systems designed to support stock investment decisions with a large diversity in focus and approach. One stream focuses on asset and liability management (ALM) topics suited for professional institutions like banks which seek support for risk management comprising all of their asset classes. Moynihan et al. (2002) suggest a DSS that forecasts the amount of assets and liabilities and the primary interest rate and involve simulation models to conduct gap analysis and rate risk of the institution. Additionally, it is possible to run "what-if" scenarios to analyze developments under changing market conditions [32]. A more recent approach utilizes complex stochastic programming methods to support optimal strategic asset allocation providing a user-friendly web interface [6].

In regard to the topic of stock investment, the majority of previous research strives to provide better insights to investors by improved information support. Methods to model stock price development using optimization or machine-learning approaches are commonly used. Specifically, artificial neural networks show broad coverage in investment decision support literature, often in combination with other approaches. Tsaih et al. (1998) combine a neural network approach with a static rule base to predict the direction of daily price changes in the S&P 500 stock index futures which outperforms a passive buy-and-hold strategy [43]. Chou et al. (1996) follow a similar approach for the Taiwanese market [12]. Liu and Lee (1997) propose an Excel-based tool for technical analysis [27]. Other approaches combine neural networks with genetic algorithms [e.g. Ref. 5]. Kuo et al. (2001) show that they reach a higher prediction accuracy of stock development when including qualitative factors (e.g. political effect) in addition to quantitative data [25].

More interactive forms of decision support, where systems provide a laboratory-like environment for prospective investors to conduct standard as well as customized analyses, have appeared. Dong et al. (2004) suggest a framework for a web based DSS which implements a comprehensive approach to the investment task up to rebalancing an investor's portfolio according to his risk/return profile. They integrated On-Line Analytical Processing (OLAP) tools for customized multidimensional analyses [16]. Another approach for interactive investor support provides the possibility of stepwise model generation such that investors can start with simple models from a toolbox and incrementally add more building blocks to arrive at more complex prediction models

[2] http://caps.fool.com/.
[3] http://www.sharewise.com/.