Academic Research Project

OneSixtyTwo Labs

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Abstract

The purpose of this project is determine the information content of analyst decisions and leverage this information to produce new strategies for asset allocation. We will begin by studying the effect of market regimes on analyst performance and predictive ability. Next, we will construct a portfolio based by matching the buy decisions of these analysts. Finally, we propose a machine learning (ML) algorithm for determining whether to invest into active or passive portfolios. The primary innovation of this approach comes from the use of a Bayesian alternative to XGBoost called NGBoost (Duan et al. 2019) which allows for a degree of belief in parameter fits, including in the model the idea of missing information inherent in financial modelling.

Analyst Stock Selection Skill

- **Market Regime Identification:** There is already significant research towards the use of various regime-switching models in finance. Popular examples include hidden Markov models (HMM) Mamon and Elliott (2007)} and autoregressive Markov switching models (AR-MS) (Haas, Mittnik, and Paolella 2004) many of which can be adapted to sector specific cycles. Work has been done to model interest rate cycles (Ang and Bekaert 2002), business cycles (Duprey and Klaus 2017) and volatility regimes (Rossi and Gallo 2006; Haas, Mittnik, and Paolella 2004). However, this often requires underlying distributional assumptions about the data and does not allow for the ML algorithm to discern its own patterns. Furthermore, it is critical to determining the number the regimes for the model (Psaradakis and Spagnolo 2003; Pohle et al. 2017). Machine learning algorithms can provide a better alternative, since they avoid the distributional assumptions required and can often detect high dimensional behaviour which is difficult for users to observe. Some interesting examples of ML algorithms which utilize regime switching include Threshold Recurrent Reinforcement Learning (Maringer and Ramtohul 2010) and Regime Recurrent Reinforcement Learning algorithms (Maringer and Ramtohul 2012). Additionally, there are some promising results using PCA and ML clustering algorithms which might be able to detect more micro-regimes.
- **Ranking Analysts:** After a suitable differentiation of various market regimes has been determined, the available information can be separated. Our primary goal will be to rank analysts in various sectors/regimes extending previous work~(Stickel 1992; Clement 1999). Our goal will be to fit these metrics under a Bayesian framework to capture our degree of belief in various rankings. Any future strategy can leverage this degree of belief in an analysts ranking to mitigate risk. Furthermore, top ranked analysts have been shown to encourage herding improving their performance (Cooper, Day, and Lewis 2001), while non-leading analysts recommendations appear to have minimal impact (Loh and Stulz 2010). Strategies we implement should leverage this information.
- **Portfolio Construction:**
  Once analyst rankings have been determined, we can construct trading strategies that utilize their information, as well as the herding behaviour they encourage, under various regimes. The proposed model of selecting analyst buys in outperforming sectors, and a classical model like Black-Litterman, can both be used as benchmarks for other alternative methods. Researchers have been able to construct

strategies that predict and leverage earning surprises (Snow 2019) as well as the impact of rating changes (Barber, Lehavy, and Trueman 2010). Both illustrating that there is an important informational content in analyst decision making.

Active Strategies

Our previous work would make it possible to determine which managers are most likely to outperform the market, as well as which market regimes are most conducive to outperformance. However, as illustrated in (Snow 2019), machine learning algorithms have higher performance when they are able to leverage the information content of human decision making. It has also been established that ML algorithms have a superior ability at detecting structure in noisy data making them a perfect candidate for portfolio construction. Therefore, our goal will be to construct a ML algorithm which will utilise aggregated analyst data in order to recommend stocks it believes will outperform the benchmark. Such a methodology should outperform mimicking analyst buy decisions or investing in active sectors with high dispersion because of the inherent properties of ML.

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