Regime Shift in Systematic Trading

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1 Introduction

The behavior of assets tends to change over time, risky assets tend to have a better performance during economic expansions, while in economic recessions, safe assets tend to outperform riskier assets.

Regime identification focuses on classifying different patterns in financial instruments behavior and/or economic variables. In this project we focused in identifying four regimes: bearish high volatility regime, bullish high volatility regime, bearish low volatility regime and bullish low volatility regime, with a non-traditional approach in order to develop regime based trading strategies.

This project deviates from the classical approach of identifying regimes with Markov Switching Auto Regressive models and instead we used XGBoost. Additionally, we developed a trading strategy based on maximizing the Sharpe-ratio for each regime.

2 Review of Literature

Traditionally, Markov switching auto regressive models have been used to identify regimes. The Markov switching auto regressive model is based on Maximum Likelihood estimation (MLE) of coefficient. The base for this model is the state equation for volatility, where using the data and MLE approach, author finds the hidden state, i.e, coefficient for those equations. These coefficients acts as proxy for different regimes

In this project we focused on replication the work of Ritabrata (2018) which not only identifies bullish and bearish markets based on a Markov Switching model, but also with the use of a triangular moving average it identifies high and low volatility regimes and develops a dynamic trading strategy.

3 Methodology

3.1 Regime Identification

3.1.1 Markov Switching Auto Regressive Model

When modeling asset prices with time series of data, many people apply autoregressive to simulate for the current state, random shocks and a regime process. Markov switching auto regressive is a model process that hold Markov property. The probability of transitioning to any particular state is dependent solely on the current state, and not on the sequence of state that preceded it. It also comes with an auto regressive component, so the output depends linearly on its previous value and AR components are part of ARMA and ARIMA.

To identify regimes we used as input the S&P 500 index.

3.1.2 Triangular Moving Average

The long term moving average is a triangular moving average (Zakamulin, 2015) which performs double smoothing of the stock prices (with 250 days period), which also means averaged twice. The triangular moving average shows the average price of an asset over a specified number of data points — usually a number of price bars. This approach enable us to better capture accurate volatility for the return movements.

Putting the moving average and the Markov Switching autoregressive models together we obtained regime identification (Figure2).

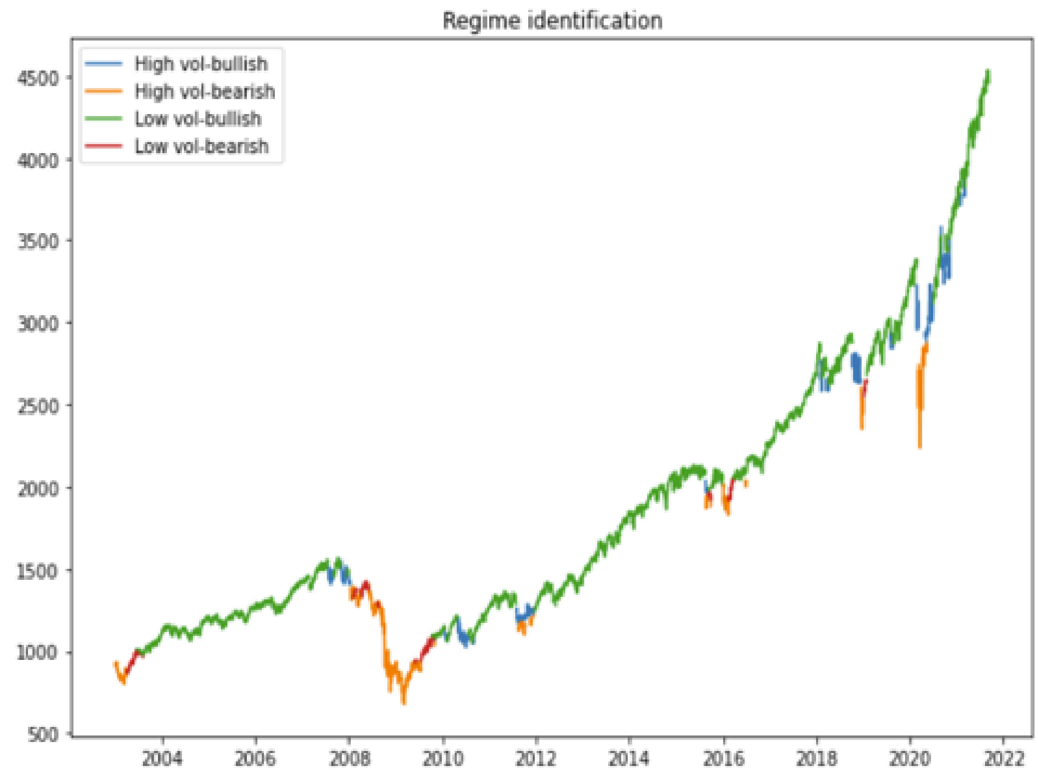

Figure 1: Regime identification

3.2 Regime Prediction

It is of great importance to detect regime shifts and adapt the trading strategy accordingly. The threshold model had been used for regime shift detection, which predicts a future shift in the market regime when the volatility and moving average reaches a certain threshold.

The four modelled regimes using Markov Switching Auto Regressive Model and Triangular Moving Average will be the predictive outcomes.

3.2.1 Regime Identification with XGBoost

We also apply Xgboost verify the regime classification results from paper. We classify the result into 4 categories, and compared with the results table in paper to establish confidence in our model based on historical returns and additional features.

3.2.2 Alternative Data for Additional Features

We would like to add more macroeconomic features to optimize our model but due to issue of frequency mismatch and having less data (low frequency). Eg - GDP is quarterly metrics.We read few articles and found that we can have high frequency data (daily frequency instead of quarterly or monthly) which closely tracks the broad macroeconomic variables. Since GDP contains only a few points, we can use semiconductor ETF as a proxy for GDP to train our model and improve classification results. We also use VIX over S&P 500 returns as VIX can represents the volatility of the price returns.

3.2.3 Feature Selection

We also check the correlations between features per segments to see if any feature is highly correlated with others. We can drop these feature accordingly to reduce noises and achieve a better accuracy of model.

4 Results

Our first aim was to verify results from the paper, i.e, using Markov switching AR model, reproduce results for regime classification and test the trading strategy. We were able to successfully reproduce the results from paper.

4.1 Deep Learning model

After that, we digressed from the paper and implemented Deep Learning models, to classify the regimes. To compare the results, we took classes from the paper and compared them against our results. Following are the results for different models used and match between paper regimes and our model regime classification.

Excluding COVID				
Accuracy ratio:	76.85%			
Confusion matrix	low-vol + bearish	low-vol + bullish	high-vol + bearish	high-vol + bullish
low-vol + bearish	0	0	0	14
low-vol + bullish	0	215	0	40
high-vol + bearish	0	0	0	14
high-vol + bullish	0	4	0	24

Excluding COVID + Housing ETF + Swap Rates				
Accuracy ratio:	84.24%			
Confusion matrix	low-vol + bearish	low-vol + bullish	high-vol + bearish	high-vol + bullish
low-vol + bearish	0	13	0	1
low-vol + bullish	0	254	0	1
high-vol + bearish	0	4	0	10
high-vol + bullish	0	20	0	8

Figure 2: XGBoost regime classification results

We had some intermediate result as well, such as before testing for correlation, without adding multiple features. But the attached ones are the most accurate model results. We see that non covid period is better classified by the model rather than covid period. But after dropping correlated features, we were able to get some clear results.

4.2 Trading Strategy

The trading strategy mentioned in paper aims at taking benefit of different regime classification and alternative weights between various asset classes to get better returns rather than static portfolio. To test the trading strategy mentioned in paper, we used results from our regime classification model and dynamically adjusted the weights between stocks, bonds and gold to back test the strategy.

Figure 3: Dynamic trading strategy

Strategy 1 is the dynamically balanced portfolio where the weights are changed according to regime, while the strategy 2 is static portfolio.

We can see that the portfolio which is dynamically re balanced, performs better than the static portfolio.

5 Conclusion

We conclude that the regime shifting classification can also be done using Deep Learning models such as XGBoost and LSTM rather than tradition MLE estimators like Markov Switching Auto Regressive models. This classification is important as different asset classes behave differently under different market conditions. We are able to verify this successfully through regime classification and strategy back tests.