Momentum-Based, Low-Noise Machine Learning Prediction: A Review of the ZigZag Modeling Toolkit (ZZ)

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Abstract — This comprehensive study delves into the sophisticated mechanics of ZigZag (ZZ), a fully autonomous momentum prediction and trading. Harnessing the power of advanced algorithmic techniques, this system employs a bespoke classifier that analyzes stock price movements, categorizing them into forward-looking upward "zigs" or downward "zags". Drawing conceptual inspiration from the Zig Zag Indicator, initially devised by trader Bill Wolfe, ZZ builds upon this work and attempts to predict the current state of the Zig Zag indicator. The Zig Zag indicator was initially conceptualized due to its ability to provide a single stock metric dictating if the stock is in an up-swing vs. a down-swing. The limitation with the Zig Zag indicator is it is backwards-looking, and requires T + ~10 trading days to properly compute. This means the Zig Zag indicator can only be used for historical assessment purposes only, limiting its real-world potential. To overcome this limitations, ZZ was built to predict the Zig Zag indicator as a forward-looking tool. If successful, it can predict if a stock is in a long-term upswing or downswing.

In addition to the theoretical usage of the Zig Zag indicator, ZZ is built for live, automated, headless trading. ZZ is engineered to execute buy orders upon the detection of two sequential positive "zigs," while initiating sell orders following the identification of two consecutive negative "zags." This paper discusses the architecture of ZZ, detailing the methodologies, feature selection, and performance evaluation metrics utilized in its development.

In an effort to quantify the effectiveness of ZZ, we have conducted extensive empirical analyses, incorporating diverse market scenarios and volatility regimes. The Core model achieves an accuracy of 71%, area under the curve (AUC) of 77% and F1 score of 78%. In a backtest scenario over a 1 year period, ZZ achieved an alpha of 1,900bp vs. a simple buy-and-hold strategy.

I. Introduction

In the evolving landscape of financial markets, the surge of algorithmic trading has markedly transformed the dynamics of trade analysis. This paper introduces ZZ, a cutting-edge automated trading system that adds to this technological evolution. The system implements a sophisticated classification algorithm developed specifically to predict the Zig Zag Indicator, a backwards-looking technical indicator that cuts through all market noise and returns a simple +1 for an upward stock movement (zigs) and -1 for a downward stock movement (zags). By eliminating noise and being a longer-term focused indicator, it provides an excellent ground-truth for our predictive classifier. ZZ incorporates the proprietary classifier and live-trading tools to implement the strategy.

The design and implementation of ZZ are explored in this paper. The classifier used in ZZ is built on advanced machine learning models, particularly leveraging the capabilities of gradient boosted decision trees to enhance the accuracy of trend detection. ZZ sits within the broader context of momentum trading strategies, which have historically challenged the Efficient Market Hypothesis by demonstrating that public domain data can indeed be useful in determining future returns. The system's ability to search through the "noise", when trained on the right end-target, provides it real-world applicability. Furthermore, we explore the economic and statistical significance of ZZ through rigorous empirical analysis and backtesting. Through an evaluation of ZZ's potential as a strategic tool, we aim to advance the understanding of algorithmic trading and its role in capitalizing on market anomalies and enhancing trading performance.

II. ZigZag Indicator

The Zig Zag Indicator, a technical analysis instrument devised by the renowned trader Bill Wolfe, is adept at filtering out market noise to accentuate pivotal price changes. Unlike conventional forecasting indicators, the Zig Zag Indicator does not attempt to predict future market movements. Instead, it serves as a tool for simplifying and clarifying the visualization of historical price movements. By establishing a predetermined threshold for price movement (e.g. 5%), this indicator interconnects significant price peaks and troughs, thereby forming a distinctive zigzag pattern that effectively omits inconsequential fluctuations. It is this foundational principle that underpins the ZZ's sophisticated trend classification mechanism. The challenge with this indicator is its backwards-looking requirements – only after several trading days (e.g. T+10) can enough data be gathered to correctly calculate the price peaks and troughs. This limits the real-world applicability of the Zig Zag indicator.

We seek to overcome this limitation by making a real-time prediction of the Zig Zag indicator. And if successful, this should create a more nuanced system of trend detection. The system is designed to identify discernible upward and downward trends—termed "zigs" and "zags" respectively—by applying a custom classifier that processes price and feature data. This allows ZZ to accurately predict the Zig Zag indicator real-time.

III. Machine learning models

The predictive framework of the ZZ system is defined by an ensemble model that integrates gradient-boosted decision trees with neural networks. This ensemble approach captures

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complex patterns and dependencies within the data, enhancing the model's predictive accuracy. Training is conducted using state-of-the-art tools like XGBoost, CatBoost, RandomForest, LightGBM, and PyTorch, all orchestrated within the AutoGluon framework to optimize hyperparameters and ensure thorough validation.

A. *Recurrent Neural Networks (RNN)*

Neural Networks, implemented using PyTorch, form the deep learning core of ZZ. These networks model complex, non-linear relationships through deep architectures that learn hierarchical representations. Designed to process both temporal and cross-sectional data, neural networks use recurrent layers for temporal dependencies and convolutional layers for feature extraction. PyTorch's flexibility allows efficient exploration of architectures, integrating features like historical data and market sentiment to enhance predictive performance.

B. *Random Forest Classifiers*

Random Forests are a robust ensemble method, creating a multitude of decision trees from random subsets of data and features, enhancing generalization and reducing overfitting. In ZZ, Random Forests add stability and diversity to predictions, capturing complex interactions without extensive preprocessing. Each tree votes on the class prediction, enhancing robustness and reducing variance, making them ideal for the model's broad feature set, including technical indicators and financial ratios.

C. *Gradient Boosted Decision Trees (GBDT)*

GBDTs are a formidable machine learning tool, adept at handling high-dimensional and non-linear datasets. They build an ensemble of decision trees sequentially, each correcting the errors of its predecessors through gradient descent, minimizing loss iteratively. In ZZ, models like XGBoost and LightGBM are employed to capture subtle patterns within financial data. XGBoost excels with its speed and regularization features, preventing overfitting, while LightGBM handles large datasets efficiently, using a leaf-wise growth strategy to create more complex models with fewer trees.

D. *Categorical Boosting Classifiers (CATBoost)*

CatBoost specializes in datasets with categorical features, crucial in financial contexts where variables like industry sectors and analyst ratings are significant. CatBoost's novel encoding methods reduce overfitting, enhancing the model's ability to learn from categorical data. By incorporating CatBoost, ZZ accurately captures the nuances of categorical data, leveraging techniques like Ordered Boosting to improve generalization.

E. *Autogluon Hyperparameter Framework*

AutoGluon is employed to streamline model training and hyperparameter optimization, ensuring ZZ operates at peak performance. This framework automates model selection and tuning, managing ensemble complexity by choosing promising models and optimizing parameters for accuracy. Supporting a variety of machine learning frameworks, AutoGluon uses advanced optimization algorithms to fine-tune each ensemble component, adapting to diverse data distributions and model configurations.

IV. DATA

ZZ utilizes an array of data sources to build a robust feature set for predictive modeling. This feature set includes price technical features, fundamental data, changes in analyst recommendations, insider trading, correlations, timeseries feature engineering, quantitative analysis and more. All-in, the system can generate 2,000+ features for all U.S. listed-stocks. Among these features, we selected the most relevant items and ended with a list of ~400.

In the end we created seven models for ZZ. During preliminary evaluations we discovered similar companies shared feature sets, and by including multiple, similar stocks into one model, more training data would be generated and this would enhance the model’s predictive capabilities. The seven models are defined as:

- **Core:** 47 of the top companies in the U.S.
- **S&P 500:** All 500 companies within the S&P 500 index.
- **Healthcare Device:** Small, medium and large-cap companies within healthcare.
- **Consumer:** Large-cap companies within consumer.
- **Defense:** Small, medium and large-cap companies operating for the Department of Defense.
- **Midstream Oil/Gas:** Small, medium and large-cap companies operating in the gas sector.
- **Technology:** Medium and large-cap companies operating in the technology sector.

Overall, ZZ was trained on ~1,000 companies, with each company providing over 10 years of data. Using daily trading intervals, this provides us 2.0M datapoints to build the classifier. Across all data, the target variable is two outcomes: 1 for a positive movement in the Zig Zag indicator or -1 for a negative movement in the Zig Zag indicator.

V. MODEL PERFORMANCE

A. *Performance Metrics*

For each training dataset, the data was split 20% for tuning data and 10% for testing data. Each of the seven models were ran separately and performance scores on un-seen test data calculated. The results are as follows:

Model Name	**Performance Scores**		
	ROC AUC	***Accuracy***	***F1***
Core	0.77	0.71	0.78
S&P 500	0.78	0.73	0.78
Healthcare	0.77	0.70	0.72
Consumer	0.77	0.70	0.74
Defense	0.78	0.73	0.79
Midstream	0.79	0.78	0.85
Technology	0.76	0.71	0.77

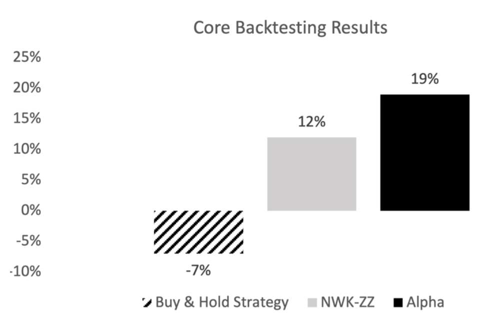
Among each model, performance for the individual constituents were also calculated. These scores are not as meaningful as the whole model performance, but offer an interesting look into the inner performance on a stock-by-stock basis. Results for the core model of the top three and bottom three stocks are:

Model Name	Performance Scores		
	ROC AUC	***Accuracy***	***F1***
SPY	0.85	0.85	0.91
HD	0.85	0.77	0.82
CAT	0.85	0.76	0.82
…	…	…	…
AVGO	0.71	0.59	0.83
UNH	0.71	0.69	0.74
TSLA	0.69	0.63	0.69

B. Backtesting

Using the trained classifier, backtesting was performed and evaluated. Backtesting used a buy-and-hold strategy as the benchmark. From a time period of September 20, 2023, to July 16, 2024 the buy-and-hold strategy generated performance of -7%. Over the same time period, ZZ achieved a performance of 12%. This results in alpha of 1,900bp vs. the buy-and-hold benchmark. Reviewing the backtesting results based stated model performance, we calculated 24bp of alpha per 100bp of AUC, 28bp of alpha per 100bp of accuracy and 28bp of alpha per 100bp of F1.

Figure 1. Model Backtesting – Alpha Generation



VI. Trading Strategy Implementation

ZZ was built for live-trading. In addition to training and re-training the models, ZZ was designed to 1) accurately identifying "zigs" and "zags", 2) trigger a buy order upon detecting two successive positive "zigs" and 3) maintains the position until two negative "zags" indicate a sell. Trades are executed for end of day market auctions. Additional research is being conducted to further optimize this trading system and incorporate derivative approaches as well.

The entire program is constructed into a Docker container and deployed on Google Cloud. The strategy database uses Airtable, while logs are stored in Firestore. Various computational tools on AWS EC2 and Google Vertex are use for new model training.

VII. Conclusion

The ZZ system represents a comprehensive and sophisticated approach to market analysis, utilizing a wide array of features to predict the future result of one indicator: the Zig Zag. By focusing on this one indicator, a proper trading system can be designed to effectively filter market noise and enhance trend classification, resulting in more accurate and reliable trading decisions. As demonstrated, ZZ has a competitive advantage in detecting significant market movements and can be used to optimize trading strategies.

Through empirical evaluation, ZZ showed impressive results. With an effective backtesting period spanning from September 20, 2023, to July 16, 2024, ZZ produced a performance outcome of 12%, contrasting sharply with a -7% result from a traditional buy-and-hold strategy, thus exhibiting a significant alpha of 1,900 basis points. Performance metrics from the individual models further underscore ZZ's robustness; accuracy, AUC and F1 scores range from high-70s to low-80s. These metrics indicate not only the model's capacity to generalize across diverse sectors but also its ability to deliver consistent outperformance driven by strong predictive capabilities.

Central to this success is ZZ's extensive dataset and feature set, encompassing over 2.0M datapoints derived from 10 years of historical data covering more than 1,000 companies. This includes price technical features, fundamental data, quantitative entities and a comprehensive array of other data dimensions. Even among individual constituents, the core model achieved strong performance, exemplified by top stocks like SPY and HD reaching high ROC AUC scores of 0.85. Such results illustrate the model's granularity and its adeptness at stock-specific analysis.

Future iterations will aim to integrate additional data sources and enhanced feature sets, refining performance and adaptability. This includes harnessing new technical indicators and integrating macroeconomic data or alternative datasets to bolster predictive power. The ongoing development of ZZ builds upon others tools utilizing cutting-edge technology and data science methodologies to propel the study of finance and investing. ZZ demonstrates a new tool to improve trend prediction, seek stronger trading outcomes and maximizing returns in ever-evolving financial markets.

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