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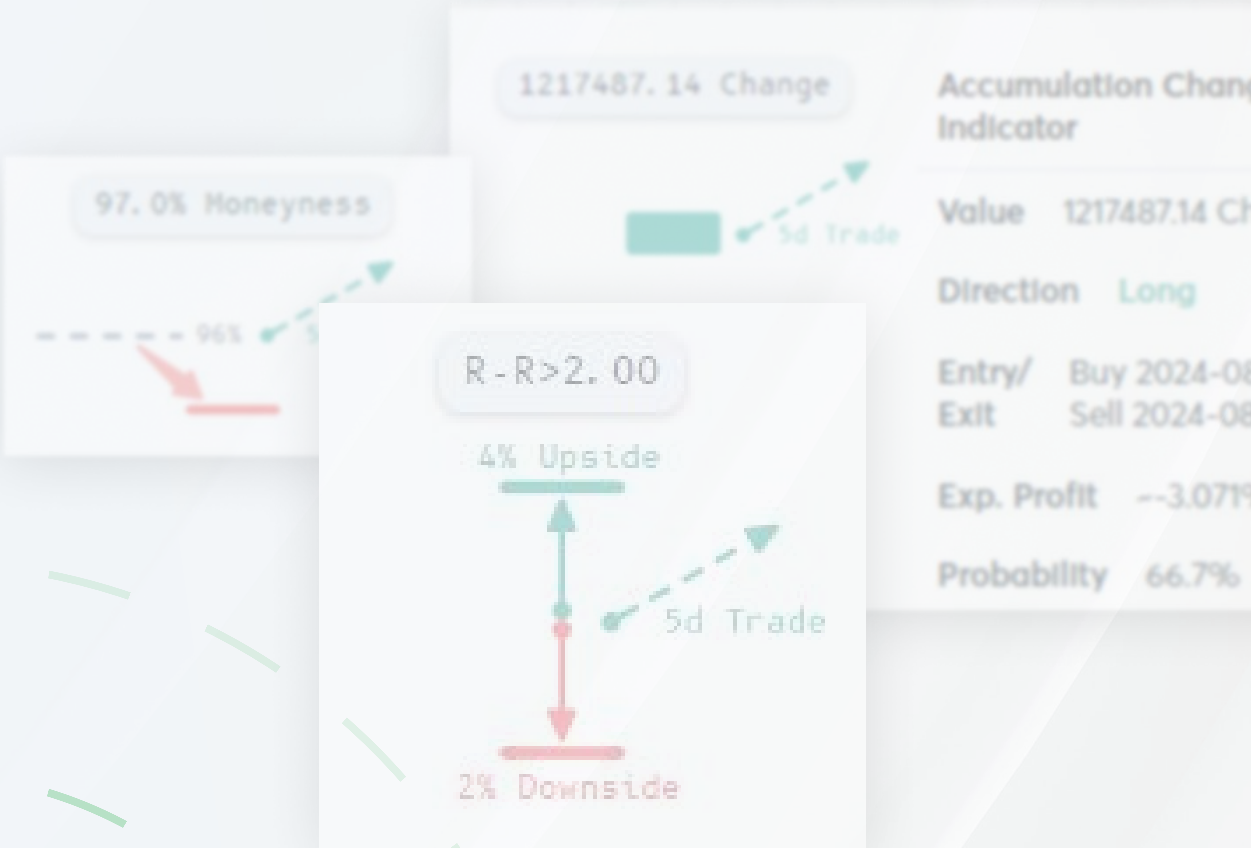
Model Validation Report



By Professor Ali Dadpay, Ph.D

September 2024

Summary

Validation is an important element of creating machine learning models. The whole idea of this is to verify the logic, results and deliverability of models, especially those used for financial benefits.

I have received the code and samples of raw data from Visual Sectors and repeated all the pre-processing, normalisation and analytical algorithms used there. I hereby confirm that the approach implemented is at the top end of the data practices.

I then used the sample data to get results on different test periods inside and outside of the learning sample. My calculations have **confirmed** that Visual Sectors models **deliver strong returns**, their declared hit ratio (i.e. win rate) is delivered on multiple occasions and the risk profile of strategies allows to trade stocks with **a valid mathematical expectation of positive returns.**

The indicators developed not only show solid financial performance but are also a significant improvement on the available publicly empirical research, further clarifying the industry's understanding of the stock-option correlations.

The amount of effort invested by Visual Sectors to deliver accurate, trustworthy and stable models is matched to top financial institutions.

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About Dr. Ali Dadpay

Dr. Ali Dadpay is a data analytics and econometrics expert with over 20 years of experience. As an associate professor at the University of North Texas Health Science Center, he develops courses in economics, finance, and predictive analytics, and applies quantitative methods to real-world problems.

His research focuses on multinational markets and public health economics, examining government policies and industry liberalization. He has taught various subjects, including international financial markets, banking, and labor economics.

Dr. Dadpay's work is published in academic journals such as the Journal of Econometrics, Comparative Economic Studies, and Applied Economics Quarterly, as well as media outlets like Al-Monitor.com.

General Approach

Visual Sectors have chosen to open options data to retail investors without any significant options trading knowledge and experience. The idea behind the data effort is to find specific directional indicators of stock moves based on analysing options activity. The models are targeting so-called swing trades (several days to several weeks duration of trades).

I have studied the available empirical and theoretical research published in trustworthy media. I have used the SSRN (Social Science Research Network) database that helped me identify 12 papers on the topic.

The studies (list enclosed) have focused on specific attributes of options data and correlations with market events. Volatility, Option-Strike dispersion, Option volume, Option/Stock volume, Option market sidedness, Volatility smirks have been proven to have some predictive capacity and descriptive information for trading decision making.

Studies are spread across 2 decades (from 2000 to 2020) and are well known and used by institutional investors to build hedging strategies, quant models etc.

The research papers have been published by academic researchers (M. Donders, R. Kouwenberg, T. Vorst from Erasmus University Rotterdam; C. Zhu from Hong Kong University of Science and Technology; K.B. Lovelace and A. Fodor from Ohio University etc) as well as industry professionals (R. Zhao from Blackrock etc.)

This creates strong grounds for further model development and empirical search that has been performed by Visual Sectors.

The company's study follows the highest standard of data science and delivers the expected results of sourcing predictive insights from options data to build strong swing stock trading patterns.

Data Sources and Licensing

Visual Sectors have provided licensing agreements with OPRA (Options Price Reporting Authority) and Standard and Poor's Global Intelligence.

OPRA data is delivered via authorised vendors CBOE (Chicago Board of Exchange) and Polygon.io both licensing the data for commercial use.

Market quotes and other stock information are received from Polygon.io, an authorised partner of both SIPs. SIP is a Securities Information Processor — a certified organisation that collects data from all exchanges like Nasdaq and New York Stock Exchange.

Takeaway: Data sources are valid and legit

Data Processing and Normalisation

One of the biggest challenges of building trading models is the quality of raw data. Despite it being a multi-billion-dollar market, the amount of errors delivered by vendors is astonishing.

Some tickers have recorded more than 5% of data points incorrectly.

Some of the most common mistakes were:

- Bad date format
- Missing values
- Missing or misplaced decimal points

Visual Sectors' code has reduced the number of mistakes to 0.25% which allows for **higher accuracy** of the further calculations.

Then the data needs to be normalised in order to reduce the effect of noise on the models' performance and transform data points to the same standard formats.

Takeaway: Data processing was performed to the highest standard

Feature Development

To create any model data scientists require entities to analyse. With financial markets every simple approach has been studied and exploited, so the only way to move forward would be create new entity groups with multiple entity variations. Visual Sectors call them Features.

Features are grouped into most commonly mentioned and used:

- Volatility group including implied, realised volatility in several variations including idiosyncratic calculations to support future calculations of alpha
- Fama-French effect group, a 3 and 5 factor asset assessment methodology
- Volume group including different metrics of stocks and options volume and their ratios
- Moneyness group of features describing accumulations In the money, out of the money and at the money for options contracts and ratios with other features
- Technical indicators group of features adding SMA/EMA, RSI and other technical features
- Greeks group of features describing change, liquidity measures etc.
- Open interest, strike dispersion and other descriptive features

A total of 316 features were created and used for model development at a later stage.

The logic of creating those features is in line with fundamental research, market practices and deeply understood by the data science team.

After creating those features, Visual Sectors' data and engineering team have transformed them for better and smoother model results.

Transformation included:

Outliers Treatment

The presence of extreme observations can also diminish the signal-to-noise ratio of a ML model. Method: Winsorization.

Log, Power and Automatic Transformations

Family of parametric transformations to map data from any distribution to gaussian distribution.

Non-Parametric Transformations

Non-parametric transformations to map data from any distribution to gaussian distribution.

Scaling/Rescaling

Features rescaled into the range between 0 and 1, yet not necessarily transforming the data into gaussian shape.

Standardization

Transform from gaussian distribution to a standard Gaussian distribution (mean=1, std=1). This step is also called sometimes normalization although it is a misleading label.

After that Normality and Stationarity checks have been executed to confirm that features are ready for modelling.

Takeaway: The library of features is robust, extensive and set for outstanding institutional-grade performance

Limitation: Features are created using daily updates and can not be used for intraday modelling

Model Research

Visual Sectors have performed a feature selection research to pick the most relevant of 316 created features.

Qualitative

Qualitative analysis of the data and a deep understanding of its characteristics can significantly influence feature selection before running any quantitative analysis:

- **Main idea:** use data knowledge to create homogenous subgroups of features.
- Subgroups of features will measure similar effects e.g. features tracking ATM effects.
- In the next stage, use quantitative techniques to compare apples-to-apples (features of the same group) to decide which ones are non-significant or redundant with regards to other features of the same group.

Quantitative

Quantitative analysis of the data can introduce objectivity to the feature selection process:

- **Main idea:** Use ML and Statistics to analyse the features on a standalone basis as well as their interplay within the homogenous subgroups of features created in the qualitative stage.
- Each quantitative idea is used for each subgroup to rank the most significant features.
- Based on the ranking, the total number of features will be reduced to a number between 19 and 75 or tantamount to approximately 40.

Methods used by Visual Sectors were:

- Mutual Information
- VIF-analysis
- RFE (Recursive Feature elimination) with RF (Random Forest) approach

After the features were selected, Visual Sectors conducted a series of experiments with created features by applying a set of parametric and non-parametric models.

Parametric Models

Parametric models make specific assumptions about the underlying distribution of the data. These models have a fixed number of parameters, and the values of these parameters are estimated from the data.

- **Main Features:** Simplicity, Low Complexity (few parameters--> more interpretability) and with a well-defined functional form.
- **Main pitfall:** reliance on assumptions about the distribution of the data, such as normality in linear regression.
- **Examples:** Linear Regression, ARIMA, Lasso, Ridge, Logistic Regression.

Non-parametric Models

Non-parametric models do not make strong assumptions about the underlying data distribution.

- **Main Features:** flexibility to capture complex relationships, Higher complexity and lack of underlying distribution assumption.
- **Main pitfall**: higher complexity means higher number of parameters tantamount to less model interpretability.
- **Examples:** Random Forest, KNN, etc.

Each model results have been analysed for:

- Best predictive ability (win rates)
- Best Risk metrics (sharpe ratio—returns compared to risk-free asset benchmark, drawdowns, daily volatility)
- Alpha compared to buy and hold and benchmark buy and hold
- Performance in both learning and test samples

The robust approach led to creation of an ensemble model combining several models and, eventually, creation of 8 indicators used by Visual Sectors and delivered to customers on a daily and weekly basis.

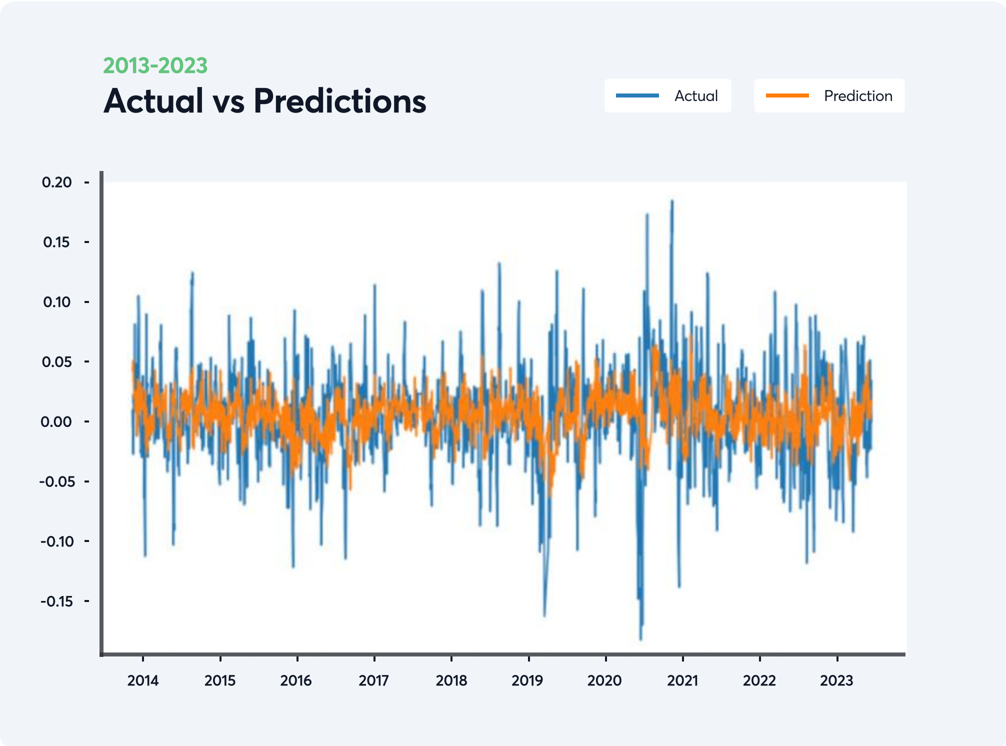
Takeaway: Model creation process is flawless and held up to the highest standards of data science

Validation

To cross-validate the features I have used the 5-fold approach. The amount of data suggests this as a sufficient level of depth.

The data sample I used covers the period between 2013 and 2023 which includes 1 recession, 3 bull markets, 2 bear markets, 2 rate cuts and 2 rate hike periods, so having 5 sets of data is proved to be enough.

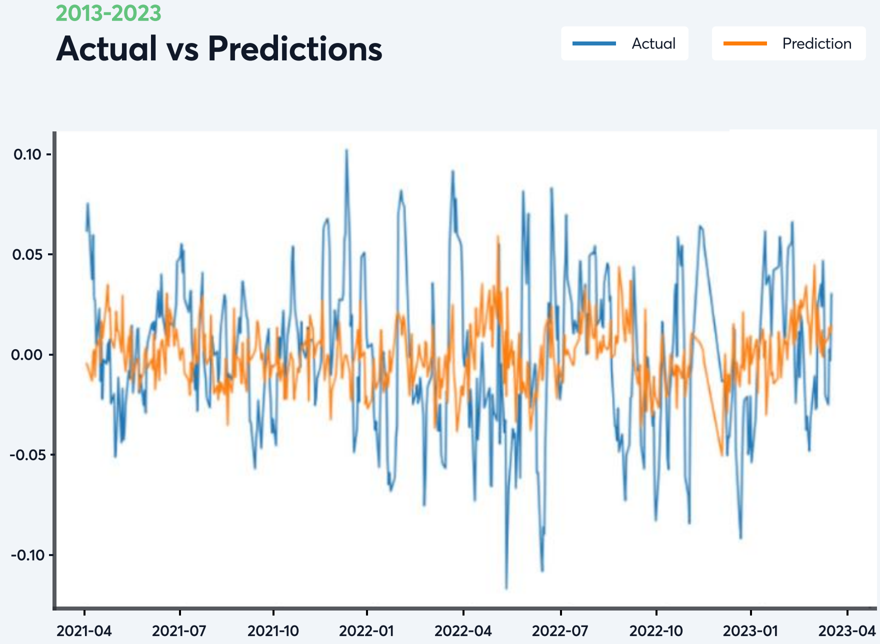
The results I have received are in line with expectations and have a solid predictive capability.



Distribution of returns number shows **clear correlation** of actual/predicted returns **over the analysed decade.**

2013-2023

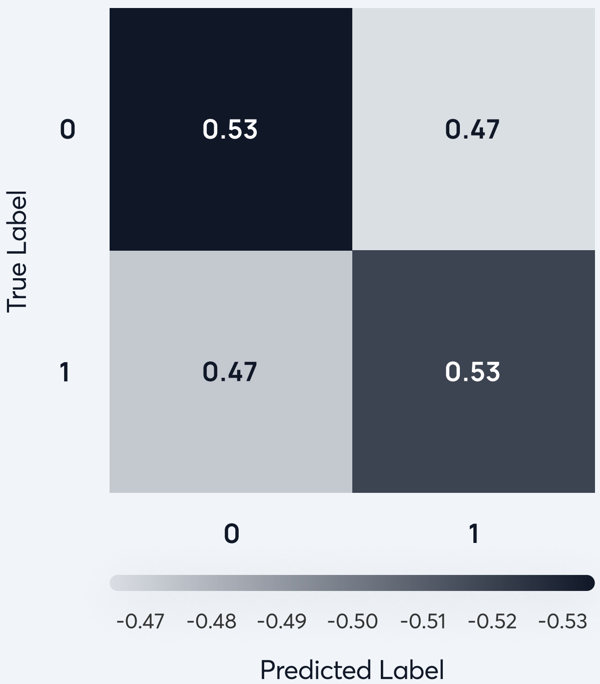
Actual vs Predictions



Distribution of returns of more recent period shows similar results.

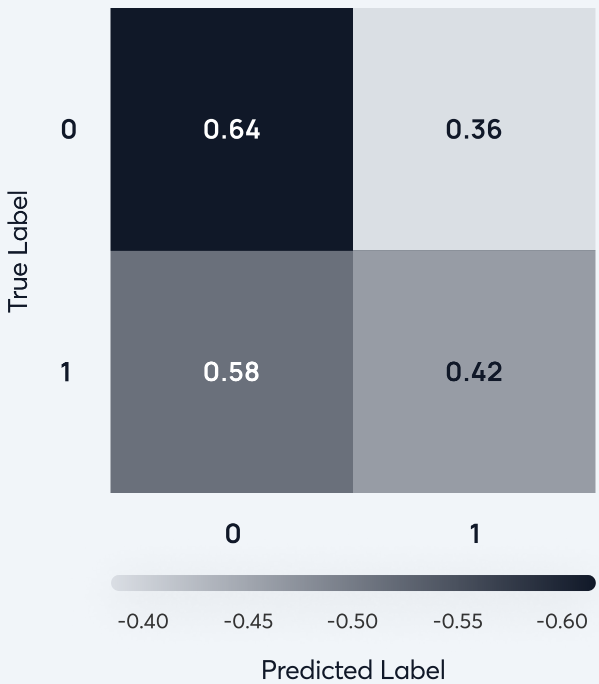
Confusion Matrix

Total Period



Confusion Matrix

Test Period



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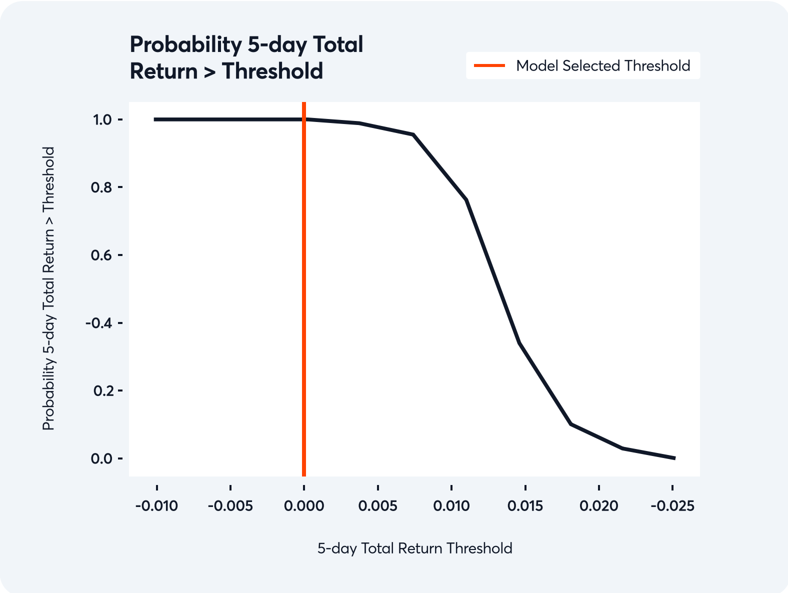
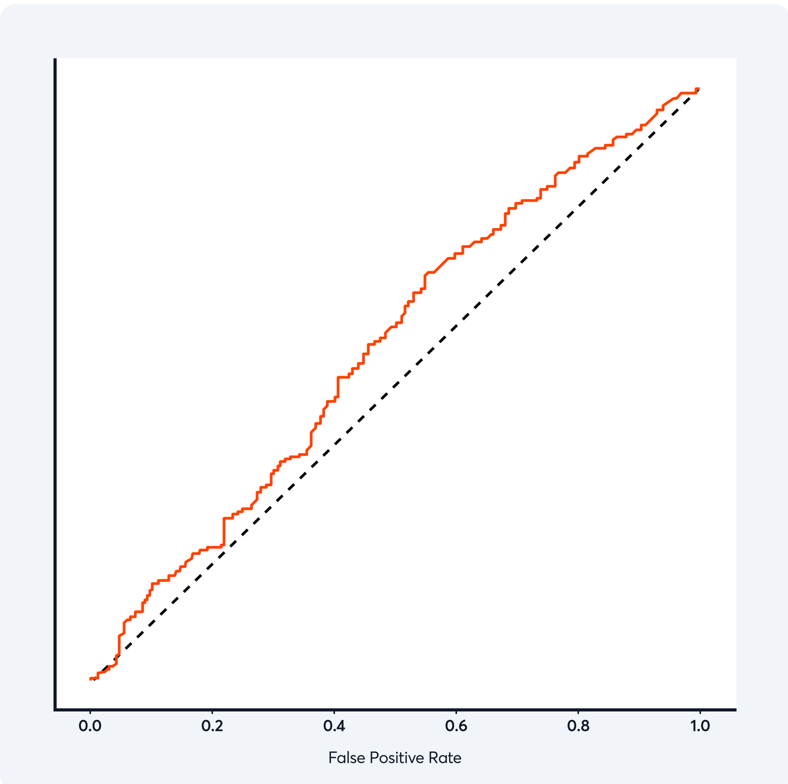
Confusion matrix returns similar results for total and test periods, keeping **prediction rates high.**



Models show best performance for a 5 day return



ROC curve, shows clear explanation of positive rate by the model with **zero false positive rates.**

2021-2023

Cumulative Return

Cumulative return of models compared to buy and hold shows significant mathematical dominance.

Takeaway: Visual Sectors models are valid, show significant mathematical probability of success. Deployment funnel is executed well.

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