My project was about applying XAI models to investing

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Machine learning techniques have recently become the norm for detecting patterns in financial markets. However, relying only on machine learning algorithms to make decisions can have negative consequences, especially in such a critical area as investing.

Investing involves making decisions about buying or selling securities based on various factors

The problematic here is: can an investor explain clearly the intuition of his position on securities ?

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So in this project, the investment task is to make prediction about the future direction of securities movements which can be upward or downward and the goal is to use "black boxes" model to balance accuracy and explainability

To do so a I developed a feature selection framework for stock returns direction forecasting that increases the accuracy of the employed Machine learning model and then I use the SHapley Additive exPlanation values to evaluate the contributions of each individual feature to the overall upward and downward movement logit probability

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I constructed the dataset by using daily historical data from yahoo finance, the data has been requested for technological stocks which are Apple and Google, over the last twenty years.

Each instance is indexed by a timestamp and characterized by the open price, close price, highest price, lowest price and volume.

Based on this information, for each stock, I created the features and the labels allowing to form the training, validation and testing dataset.

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The features are technical indicators which represent statistical tools and are extensively use in the literature to make investment decisions by generating signals.

I construct eight of them to identify trends, regime switches, momentum and potential reversal points in the stock market.

By combining these features with different time windows, I obtain a total of 17 features.

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The label is a binary variable given by the price direction.

The price direction corresponds to the sign of the difference between the price at t and the price at t -1

It is therefore used to predict upward or downward movements in the market.

Then the direction's predictions of the model are transformed into investment positions, for example If at time t the model predict 0 which means upward then position in t is equal to 1 otherwise it is equal -1

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The features have been scaled within the range (0, 1) by applying a MinMaxScaler fit on the training set, which allows to un-biased learning and ensure that each feature contributes equally to the decision-making process

I used a training split corresponding to the first 70% time series instances, while validation and testing are 15% (2017 to 2019 and 2020 to 2022)

The validation part is used for the feature selection process

The testing part evaluate if this selection has improved the performance of the trading strategy and accuracy

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In the forecasting process, I have considered Random Forests which can handle noisy and outliers instances, as a consequence of bagging and random feature selection which is useful when working with financial price data

To achieve optimal performance for each stock, some hyper-parameters have been tuned by using : a cross validation approach (TimeSeriesSplit) on only the training set with the full set of features and by maximizing the accuracy score

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Based on the optimal hyper-parameters, I train multiple RandomForestClassifier using either the full set of features or only filtered ones. The model associated with the full set of features is the baseline and will be the benchmark for performance comparisons.

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In the experiments I judged the performance of these models according to different metrics such as the accuracy, f1-score, AUC, brier-score.

However, the good performance of these metrics is not necessarily correlated to a good financial performance

Hence, I developed a trading strategy whose performance provide a complete picture of the model's financial performance

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The feature selection phase aims at assigning importance scores to features in order to identify features that are uninformative for this prediction task and to propose them for deletion

Four methods were used: the Impurity importance, the permutation importance, the lime importance and the SHAP importance

Their common properties are : (i) it is model agnostic, which means that it can be applied to any tree-based model, (ii) it computes the feature importance on validation set, which makes it possible to highlight which features contribute the most to the generalization power, (iii) it has no tuning parameters.

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My removal strategy was to compute the feature importance value on the validation set with each of the proposed method by using the baseline classifier and I stored the features having the lowest importance. This set of features formed the removable feature space and for each combination inside this space, a RandomForestClassfier has been fitted without these features and I compared its validation accuracy with the one of the baseline.

Hence, for each of the proposed method, I was looking for the combination of removable features that led to the largest increase in accuracy over the validation set. Once found, the respective RandomForestClassfier has been evaluated on the test set.

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By looking at the results for Apple, we can see that the:

Lime and Permutation method increased the validation accuracy, compared to the baseline.

However, only Permutation method allowed to have a positive outperformance of the trading strategy of 73% (seventy three percent) compared to −115% (minus one hundred fifteen percent) for the baseline.

On the testing set, each feature selection method increased the accuracy and trading outperformance

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Now by looking at the results for Google, each feature selection method allowed the accuracy and trading outperformance to be increased on the validation and testing set, which is encouraging.

Overall, Theses methods introduce clearly improvements both in terms of predictive and financial performance and the permutation method is the one that worked the best.

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Quickly, we can see that the trading strategy with the permutation method on Apple and Google (in green) outperforms the naïve market benchmark (in blue)

Therefore using such feature selection method allowed to provide long-short predictive signals whose information content suffices and is less noisy than the one embedded in the full set of features.

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In the second part of my project, I used the Shapley values as a means to interpret the impact of individual features on the likelihood of an upward movement occurring

For each stock, I analysed the testing predictions of the model built with the permutation feature importance method as it was leading to the highest testing accuracy

By doing so, we can infer the contribution of each feature to the upward or downward movement

But we have to note that as the models have only a maximum accuracy of 0.53 on testing, then some Shapley value don’t reflect the true contribution

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So this graphic represents the SHAP summary plot of Apple testing predictions. We can see that the direction features seem to be the least significant, as they may not provide a significant signal since the Random walk theory suggests that changes in asset prices are random

The most significant feature to a downward movement is ATR which measures market volatility, In general, a high volatility is an indicator of a bear market, however here we can see that low and high ATR values induce negative SHAP value

MACD which stands for Moving Average Convergence Divergence has a linear trend to the upward probability direction which seems to be related to the literature. Indeed, when the MACD value is high, it generally indicates that the bullish momentum is strong and the price of the financial instrument is increasing

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For Google, we can observe that the higher the values of Williams%R, STOCK and ChaikinMoneyFlow the higher they contribute to a downard probability direction.

In the literature, high values for these indicators indicate an overbought condition in a financial instrument, which may be an indication of a sell signal

Overall Shapley values allow for a global understanding of the model behaviour which has traits in common with the trading decisions of an investor relying on the literature of technical indicators and market factors

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This works shows that automatic feature selection is a possible solution to promote greater reliability and robustness in explainable artificial intelligence

It also emphasizes the importance of understanding the global predictions of AI models through feature's contribution to the upward probability movement

However, we must be careful not becoming overconfident about the forecasting ability of the model as it is generating often false positive and false negative signals.