Infinitech Pilot 6: Executive Summary

Personalized Investment Recommendations for Retail Customers

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1. Introduction

This is a short executive summary of research, development and testing, as well as insights regarding Infinitech Pilot 6. The document aims to provide a high-level overview of what was done, what outcomes were produced and what can be learned moving forward. It is written by the technical team who worked on the pilot at the University of Glasgow (UoG), and is primarily designed for consumption by staff at the end-user organisation at the National Bank of Greece (NBG).

2. Motivation and Solution

NBG Retail Investing: Currently, when a financial advisor sits down with a new or existing investor, NBG's current digital services only provide customer details (name, questionnaire data and past investments, if any). It is then left to the financial advisor to recommend assets to the customer to invest in. The advisor may recommend assets currently being directly promoted by NBG or help the customer find assets that fit that customer's needs.

The Issues:

- The financial advisor needs to rely on third party services to find relevant assets for the customer and/or judge their suitability.
- There is no means to pool knowledge across customers regarding investment effectiveness for different customer segments.
- The largely spontaneous and adhoc nature of the process makes individual investments made based on advisor recommendations difficult to explain post-hoc.

The Solution: Provide NBG financial advisors with a new digital service that can recommend financial assets personalized to the customer automatically, as well as summarize key investment information regarding those assets to the advisor. In this way, the financial advisor has a starting set of assets to discuss with the customer that are not biased to the advisor themselves; the recommendations can factor in past data regarding the assets and be personalized either to customer archetypes or individual customers based on their past investment history; asset information is served by the recommendation system itself, rather than wholly relying on external tools; and advisor interactions with the solution can be logged, providing a paper-trail for investments.

3. Advisor Interface

The financial advisor interface provides a ranking of recommended financial assets for the current customer, divided by asset type (e.g. equity, fund or bond), as well as by sub-category (e.g corporate vs. government bonds). For each asset, an asset details pane can be expanded, containing a description, key factoids, pricing history and technical indicators. The advisor can directly add assets presented into a saved portfolio, or otherwise search for assets to add.

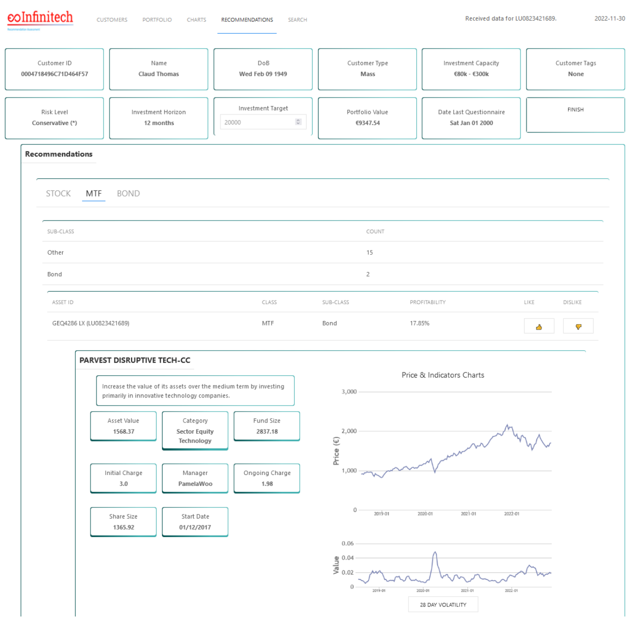


Figure 1: Financial Asset Recommendation Screen

4. Developed Technologies

To enable this solution, there are four underlying technologies that were implemented in the project:

- **FinFlink**: This component takes either historical or live streams of asset pricing data and generates asset technical indicators (such as volatility, momentum index or return on investment) for periods of time. These indicators provide evidence regarding the quality of different assets for investment, and can be visualised by the financial advisor.
- **AssetInspector**: This component takes a list of financial assets, and for each asset collects asset factual data from reputable online data sources. This is a solution to the lack of asset meta-data in NBG's databases currently, and is visualised in the advisor interface.
- **Asset Price Predictors**: A number of supervised machine learned models were trained to perform price prediction for assets at different time horizons (between 1 and 12 months into the future). These predictors use past prices and other technical indicators to make a forward projection of prices, which are the first of two means used to recommend assets.
- **Personalized Asset Recommenders**: A second class of supervised machine learned models were trained on prior investments by NBG customers. These models implicitly identify similar customers to the current customer and then recommend assets those similar customers invested in. These models are the second means used to recommend assets.

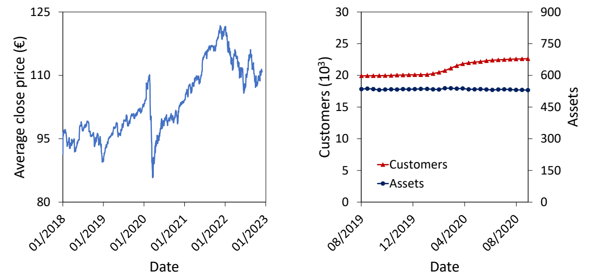
5. Data Used and Observations

During the project NBG supplied a dataset containing pricing data for a set of (predominantly) Greek assets and anonymous customer investment data. This data was cleaned by UoG and augmented using parallel pricing data collected via Yahoo Finance and asset profiles collected using the AssetInspector component. Dataset statistics are provided in Table 1:

Table 1: Dataset Statistics

Greek Market Data	
Unique financial assets	807
Assets with investments	321
Price data points	703,303
Average return (by assets, whole period)	37.16%
Asset Meta-data (via AssetInspector)	
Assets Found by AssetInspector	674 (83.52%)
...of which were Equities	231
...of which were Bonds	199
...of which were Exchange Traded Funds	244
National Bank of Greece Customer Data	
Unique customers	29,091
Transactions (unique)	387,783 (153,910)
Acquisitions (unique)	228,949 (89,920)
% Average return (by customers, whole period)	22.89%
% customers with profits	54.56%

Time Period: This dataset spans the period of January 2018 and November 2022, i.e. 59 months (almost 5 years). This period was broadly an extended bull market (predominantly due to Covid-period investment growth, [Figure 2a]), while the number of traded assets month-to-month remained roughly constant and the number of active NBG customers increased on a 15% (with the upward trend starting at the beginning of 2020 [Figure 2b]):



(a) Market Value Over Time (b) Dataset Composition Over Time

Figure 2: Market, Assets and Customers Over Time

Data Observations:

- **KYC, but not their assets?**: NBG's databases currently have good coverage of user activities with the bank, but lack information regarding the assets those customers invested in. The time-series pricing data contains notable gaps for some assets, asset events (such as stock splits) are not recorded and assets lack descriptions and key meta-data (e.g. asset categories, bond yields, or P/E Ratios).
- **NBG Customers Underperform the Market**: On average while the majority of NBG customers make money investing (54.56%), they make less money than if they had just invested in a market index fund (22.89% for NBG customers, vs. 37.16% for the market [Table 1]) over the data period, indicating that financial advice currently being provided could be improved.

6. Model the Past, Predict the Future

To drive customer recommendations, we train both asset price predictors and personalized asset recommenders for a day using data from before that day. For each day, we consider up-to the prior 18 months for training. As performance will change over time due to varying market conditions, we train models every two weeks, starting in August 2019 to the end of November 2021, i.e. performance on 29 days are tested during this period. We evaluate in two ways, averaging performance over each of these 29 days:

- **Profitability**: How much money the customer would have made if they invested in what the recommender showed them, measured in terms of monthly return-on-investment (RoI) of the top 10 assets recommended during the following six months.

- **Investment Predictiveness**: To what extent do the assets the recommender showed correlate with what the customers actually invested in over the following six months, measured using normalized discounted accumulative gain (NDCG) for the top 10 assets recommended.

7. Predicting Asset Prices

Asset prices represent one of the main sources of information to be considered in the development of financial asset recommendations, as their movements encode fundamental information about the assets and their performance. Therefore, we define and explore algorithms based on those prices.

The algorithms: We develop algorithms aiming to predict the future profitability (measured as RoI) of the financial assets at some point in the future (six months in our tests). The prediction is based on technical indicators (return on investment, volatility, momentum) extracted from the temporal pricing data. We consider three different algorithms:

- **Linear regression:** Predicts profitability using a linear function over the technical indicators.
- **Random forest:** Combines multiple regression trees for predicting the future profitability.
- **LightGBM [3]:** Advanced version of random forest using gradient boosted regression trees.

General results: We study whether regression algorithms are able to produce lucrative recommendations. Figure 3 shows the performance of the methods in terms of the monthly RoI of the top 10 recommended assets when looking at six months into the future. The figure compares the three regression models with an algorithm that randomly suggests assets, the profitability of a market index fund and the S&P 500 index fund. Results indicate that the three profitability prediction methods beat the market index during the studied period. Among them, linear regression is particularly effective – leading to even better performance than the S&P 500 fund (notably more profitable than the Greek market index fund).

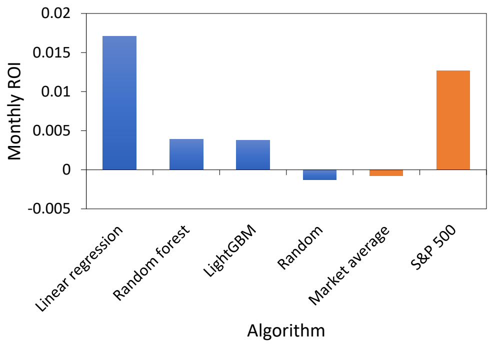


Figure 3: RoI of profitability prediction algorithms.

RoI over time: The tested period includes varying market conditions, including a notable market downturn caused by the Covid-19 pandemic. Under a bear market, the identification of profitable assets becomes a more challenging task than during a bull market. Consequently, we explore the performance of our algorithms at different points in time. In this document we limit this study to the best prediction model, linear regression, although conclusions are similar for other models. Results are illustrated in the following figure:

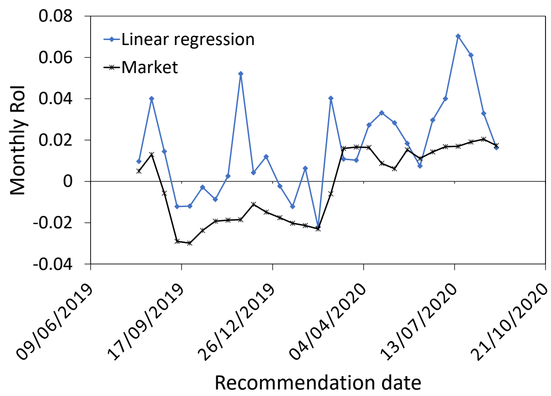


Figure 4: RoI of linear regression over time.

In the figure, the blue line represents the performance of the regression algorithm, whereas the black line shows the average RoI of the assets in the dataset. As it can be observed, the linear regression line appears, at most points, over the market line, regardless of whether the market is earning or losing value. This indicates that linear regression is able to beat the performance of a market index fund over varying market conditions – highlighting the consistency of the price prediction model over time.

Conclusions: Our tests with profitability prediction algorithms can be summarized as follows:

- Profitability prediction algorithms represent promising recommenders.
- Our methods are able to consistently beat a market index fund.
- Linear regression achieves best performance.
- Price-based models beat the market under varying market conditions (considering both bearish and bullish markets).

8. NBG Customer Insights

Investment transactions represent another potential source of information for training financial asset recommenders. The acquisition of a financial asset by a customer can be understood as an expression of interest on the asset. Therefore, we use those transactions to provide personalized recommendations to the customers.

The algorithms: We consider six transaction-based algorithms divided in three categories:

- **Non-personalized:** These algorithms aggregate transaction statistics about the assets to recommend those assets. We consider one algorithm in this group:
  - **Popularity:** Recommends the assets acquired by the largest number of customers.
- **Collaborative filtering:** Based on the principle that similar customers invest on similar assets, and similar assets are acquired by similar people. We use four widely known algorithms in this category:
  - **Association rule mining (ARM) [1]**
  - **User-based kNN (UB kNN) [4]**
  - **Matrix factorization (MF) [5]**
  - **LightGCN [2]**
- **Demographic:** These methods identify similar investors according to customer personal information. We consider one algorithm in this category:
  - **Customer profile similarity (CPS)[6]:** recommends assets on which similar customers have invested in the past. Similarity between a pair of customers is defined on answers to the risk assessment questionnaire NBG customers fill in.

Investment predictiveness: We report the effectiveness of these algorithms at predicting future customer acquisitions. Figure 5 reports performance of the algorithms in terms of the NDCG metric. Our results show that transaction-based approaches (blue bars) are shown to be better investment predictors than the random recommendation and profitability prediction algorithms (red bars) – showing that these models can infer what customers are likely to invest in.

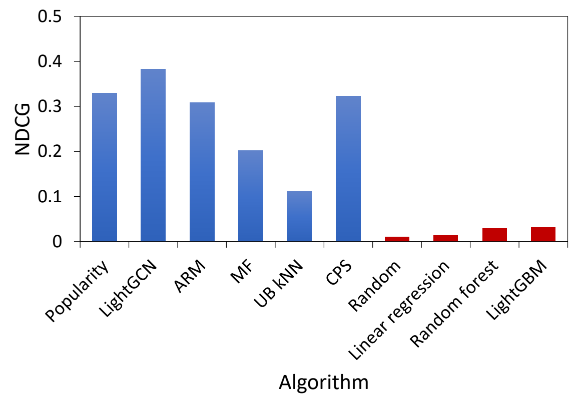


Figure 5: Investment predictiveness of transaction-based financial asset recommendation methods.

Profitability: We also evaluate whether these models return profitable assets. This is illustrated by the blue bars in Figure 6. As we can see, differently from price-based algorithms, transaction-based models do not provide profitable recommendations to the customers (in the worst case, leading to losses bigger than 2% per month).

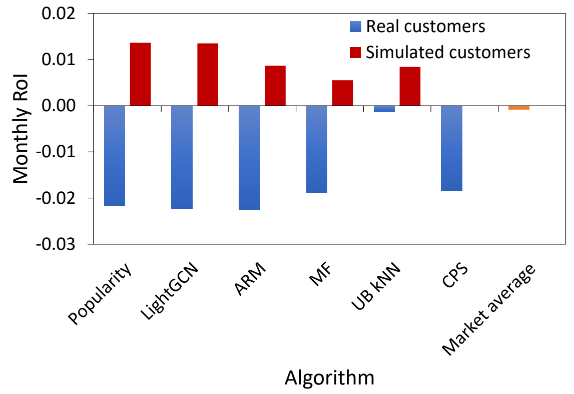


Figure 6: RoI of transaction-based financial asset recommendation methods.

The mismatch between the performance of transaction-based models in terms of investment predictiveness and profitability can be traced back to the customers' investment skills: if customers invest in suboptimal assets, our transaction-based models will learn this behaviour and replicate it. Evidence for this is shown in Figure 7, where we compare the LightGCN algorithm (in blue) with the market and the customers in terms of monthly RoI. In the figure, the LightGCN follows the same trend as the the customers, i.e. the model is only able to beat the market when customers manage to do so.

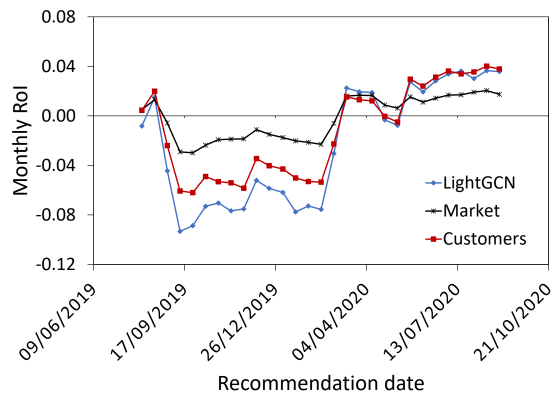


Figure 7: Market vs. Customers vs. LightGCN

What happens if our customers are good investors?: As we have seen that NBG customers are not able to navigate the market effectively during downturns, we craft synthetic customers to evaluate whether our algorithms would work if they were learning from more effective (profitable) customers. For creating those investors, we choose investment dates randomly, and the synthetic customers always choose among the 50 most profitable securities in the 6 month period following the purchase date.

Performance of the transaction-based models when we train and evaluate them with the synthetic customers is reported by the red bars in Figure 6. Compared to the performance of the algorithms over the real customers (in blue), our algorithms become capable of providing lucrative assets if training on effective customers. This illustrates that, if our customers are good investors, transaction-based model are promising methods.

Conclusions: The previous tests illustrate the following conclusions:

- Transaction-based models are able to capture customer preferences.
- But they recommend non-profitable assets.
- Transaction-based models are highly affected by the performance of the investors they train on.
- Due to the effectiveness of the customers, we cannot currently use transaction-based models.
- However, they show promise if customers become more effective.

9. Investment Horizon

Customer investment strategy represents an important factor to consider when deploying financial asset recommendations. The amount of time users expect to hold their assets (investment horizon) is an important aspect of those strategies. Different customers keep assets for varying amounts of time. For instance, around 20% of the customers hold their assets for less than a year, and 33% holc them for more than 3. This is reported in the following figure:

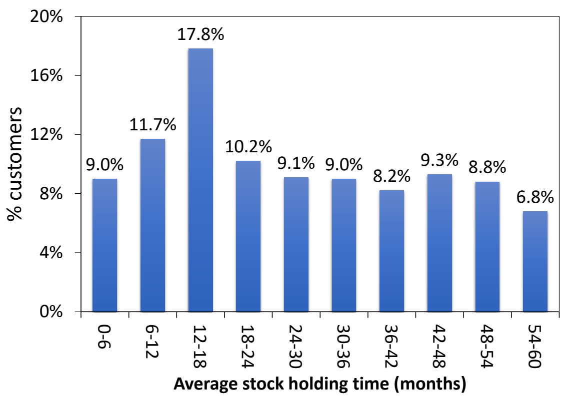


Figure 8: Average stock holding time

As customers have different strategies, we explore the effectiveness of our models (in terms of monthly return on investment) when we hold our assets for five different periods: 1, 3, 6, 9 and 12 months. We train particular models for every investment horizon. Figure 9 illustrates the results. Due to the unreliability of transaction-based models, only price-based models are reported. In the figure, the x axis represents the investment horizon (in months) and the y axis shows the monthly profitability when observing the top 10 results of every recommendation algorithm.

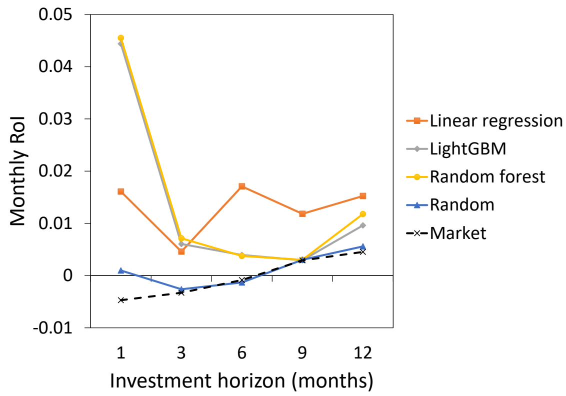


Figure 9: RoI of financial asset recommenders for different investment horizons.

Results highlight that the effectiveness of different algorithms changes depending on the chosen investment horizon: models like random forest or LightGBM perform better for identifying short term investments, whereas linear regression identifies better mid-term investments. Consequently, the investment horizon of the customer represents an important variable to consider for developing financial asset recommendations.

10. Recommendations

In this document, an overview of the work developed by UoG on financial asset recommendation algorithms has been provided. In particular, two families of methods have been proposed: price prediction and transaction-based models. Price prediction models represent promising strategies, as they are able to consistently beat the profitability of the market over varying conditions. Transaction-based models are able to better predict customer investments, but that makes them unreliable at recommending lucrative assets. Considering our outcomes, we provide the following recommendations for future steps towards the development and operation of these technologies:

- Price/profitability prediction models represent a better initial strategy for assisting customers on earning money.
- Financial asset recommendation methods should be trained and evaluated over varying market conditions. Some models might work during market upturns, but can cause customers to lose money during downturns.
- Models should be trained for different investment horizons. The best models might differ depending on the customer strategy.

11. Acknowledgements

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