Catching the Big Fish and Rising Stars Data-Driven Client Targeting at MFS

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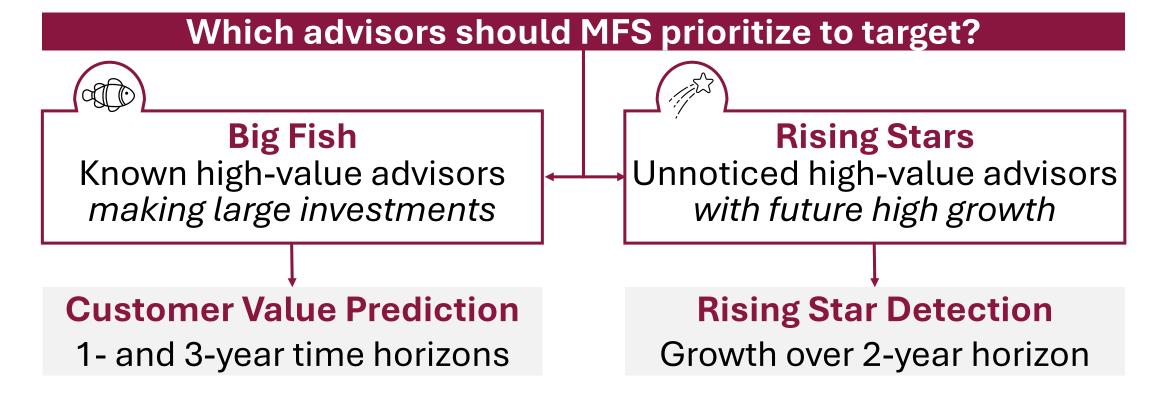




Project Overview

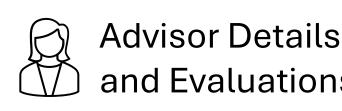
Problem Statement

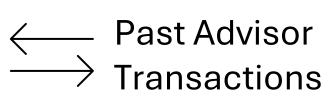
MFS sells its investment funds through **financial advisors** to end clients. While external MFS sales reps focus on high-value advisors through expensive in-person meetings, internal salespeople cover the broad base through phone calls. Since MFS' external sales resources are limited, we developed a data-driven approach to identify the "Big Fish" and "Rising Star" advisors MFS should prioritize to target (right graph).



Data

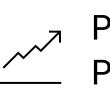
We use five datasets:











Product: MFS Client Targeting Dashboard

Our product is projected to save MFS \$18m annually by freeing up 20% of sales reps' time to pursue new, high-potential advisors identified by our models.

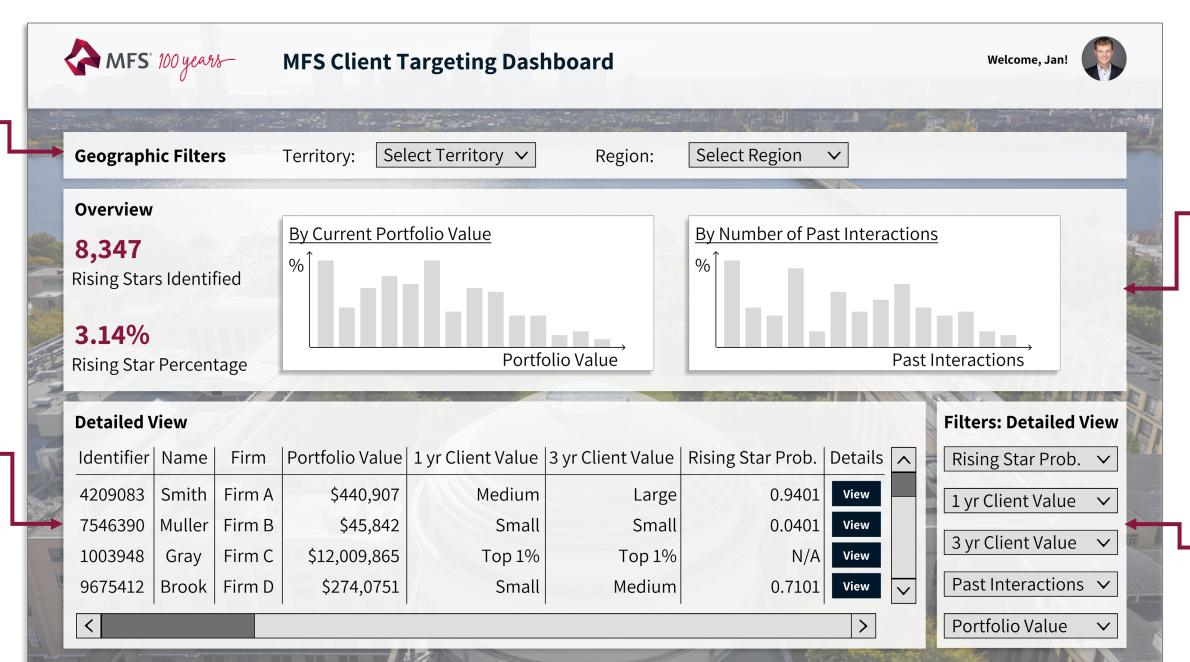
Geographic Filters

Sales reps can filter for their geographic region to see only relevant financial advisors

Detailed View

Breakdown of every relevant financial advisor by different dimensions, like:

- Current portfolio value
- Predicted short- and longterm customer value
- Rising star probability
- Past interaction count



Overview

High-level analysis with statistics and graphics:

- Number and percentage of rising stars
- Graphs of advisors by current portfolio value and past interaction count

Filters: Detailed View

Tool to facilitate customized searches by sales reps to filter for "Big Fish" and/or "Rising Stars"

1) Big Fish: Short- and Long-term Customer Value

Multi-class Classification Framework

This models' target variable is New Investment Over 1 or 3 Years, respectively. Alongside predicting continuous values, we classified <u>all</u> advisors into different classes to find Big Fish (large, top 1%) since classification aligns best with MFS' internal decision-making. Cutoff values (3 yr case) are below:



This resulted in the following classification pipeline.

Features: past investment, investment timing/ frequency, portfolio return/growth/ size, advisor metadata, ...

Models: k-NN, CART, RF, LGBM, xgBoost, Neural Nets, Log. Regr.

Predicted Class

Evaluation

1-year time horizon

84.00%

Accuracy of XGBoost (best model)

3-year time horizon

79.80%

Accuracy of XGBoost (best model)

Insights: Strongest Predictors

1 year: top 5 feature importances

New investments last year	265.5
Time since last investment	29.9
Mean time between investments	11.0
Total current portfolio value	9.8
Business unit type	7.4

3 year: top 5 feature importances

New investments last 3 years	94.4
Time since last investment	22.5
Firm size	8.7
Firm type	5.6
Mean time between investments	5.0

2) Rising Stars: Detection

Binary Classification Framework

Whether a financial advisor is a rising star will be defined based on their change in portfolio value using the following levels.



An advisor is a **rising star** if they **move up 2 or more levels** within 2 years. This binary classification framework trained on similar features is only applied to small and medium advisors.

Evaluation

Best F1-Score (Tab-Transformer):

90.20%

Best AUC (Random Forest):

92.00%

Insights: Strongest Predictors Top 5 feature importances (Rd. Forest)

Average past portfolio value 1	01.4
Overall compound growth rate 9	4.6
Current portfolio value 8	5.0
Portfolio value standard deviation 7	9.7
Time since first interaction 7	6.6



