"To Meet, Or Not To Meet, That Is The Question"

Optimizing Interaction Strategies

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Problem Statement

Company: MFS Investments is an Asset Management Company. In the Retail segment, investors entrust money to financial advisors who, in turn, come to MFS to buy financial products

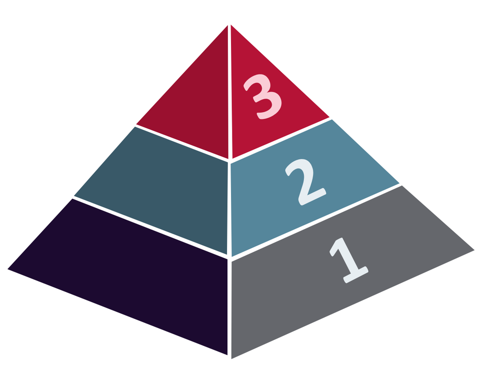
Problem: The MFS client-facing team interacts with financial advisors over time to foster a long-term relationship and to sell MFS products. Our goal is to optimize these sequences of interactions (i.e.: interaction strategies)

Data

5 years of data from multiple sources

- Past Transactions Data
- Advisor Interaction Data
- Fund Performance
- Advisor Profile Data

Approach



- **3-Step Approach:** Prepare the Data, Predict and Optimize
- **End-to-end Pipeline:** From raw data to a final recommendation
- **Modular Solution:** Blocks can be swapped and implemented independently

Prepare: Data Pre-processing → Feature Engineering

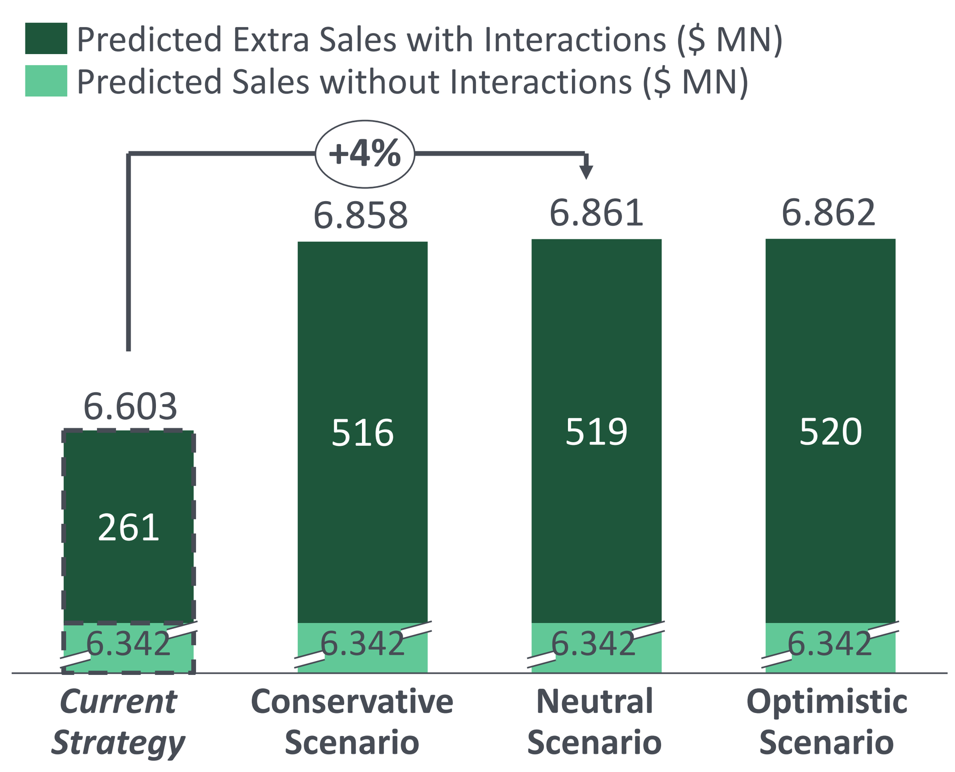
Predict: Interpretable Cross Validation → Interaction Effect Prediction

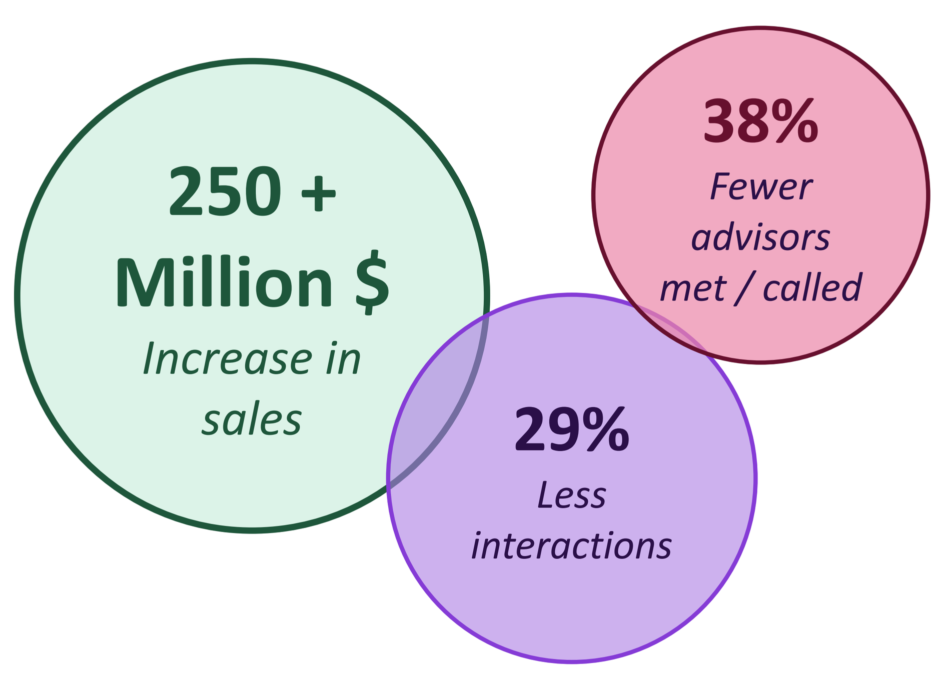
Optimize: Strategy Definition & Optimization → Tailored Strategy Recommendation

Impact

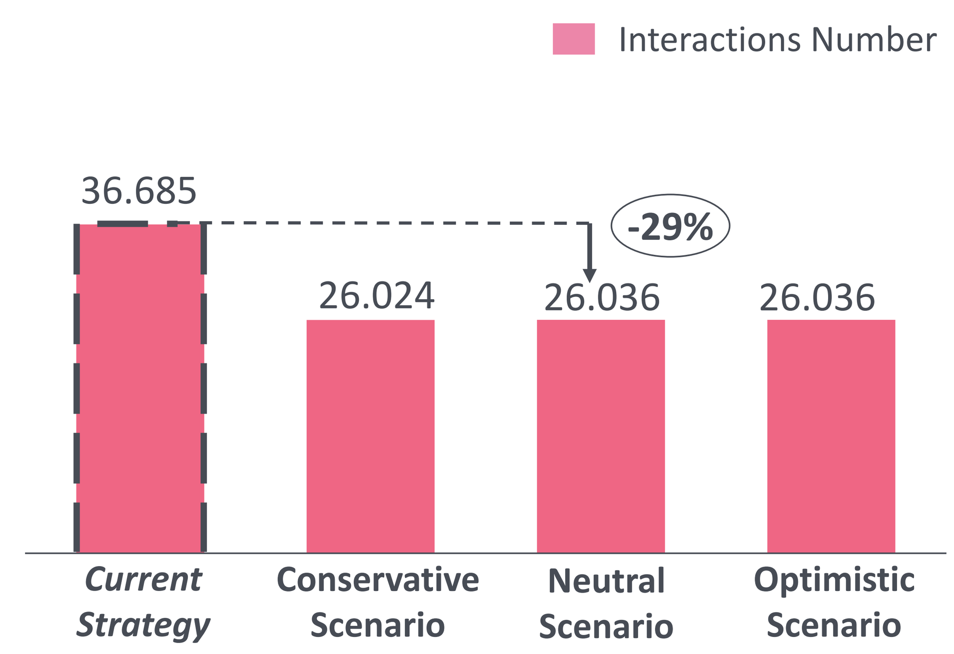
We compare hypothetical outcomes using our approach under different scenarios (i.e.: different assumptions for our optimization model) to current strategies for the main client firm of MFS.

*We observe a **sizeable expected increase in sales** in all scenarios*





*Overall, our approach shows an opportunity to make **more effective meetings and to significantly reduce calls***



Phase 1: Prepare the Data

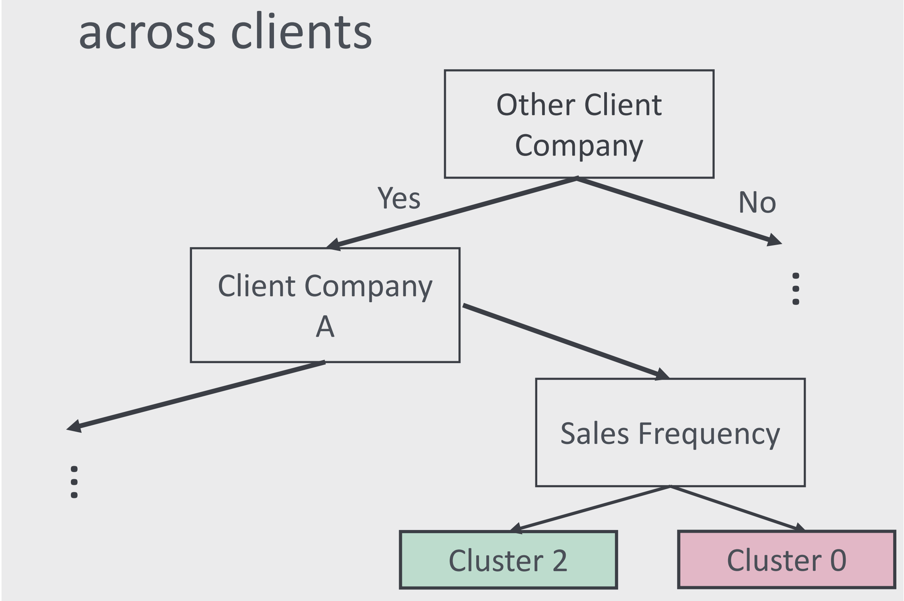
We aggregate sales and interactions by advisor for each quarter

1.5 Million records × **68 Features**

We use pretrained embedding and cater them to our corpus to impute VADER scores for unsupervised sentiment analysis

Train Word2Vec → **Impute VADER scores** → **Normalize sentiment by wholesaler**

We perform interpretable clustering to uncover similarities across clients



Phase 2: Predict Interaction Effects

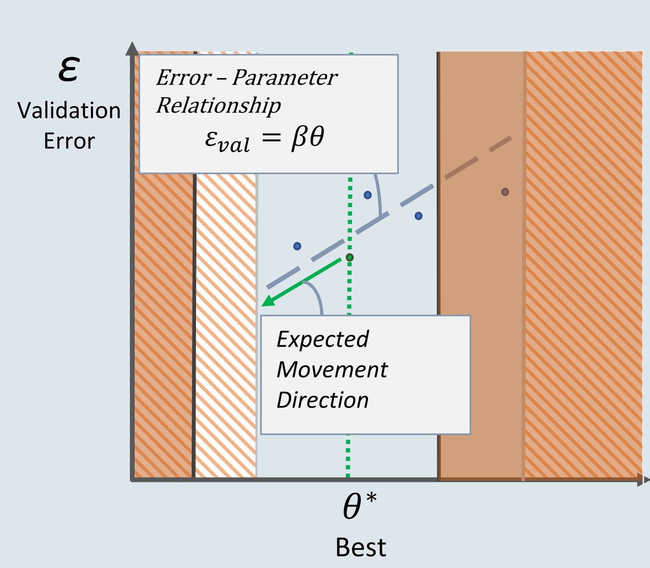
Models	Main Features
Random Forest (Selected)	Historical Sales
KNN Regression	Portfolio Returns
Decision Trees	Interaction Sentiment
XGBoost	Interaction Type
Lasso	Interaction Content (to date)

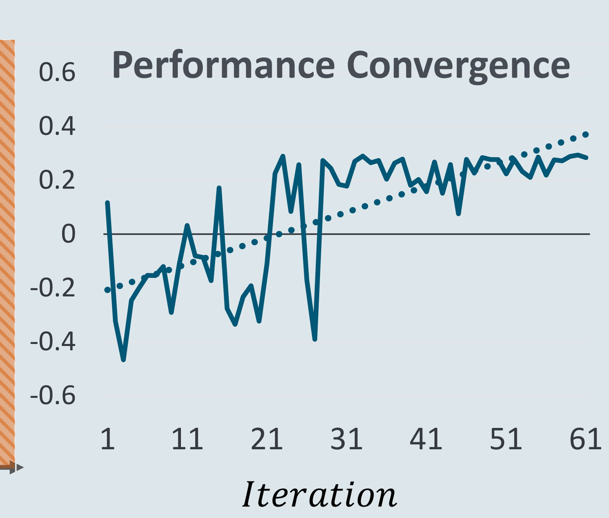
1.2x | **41% R^2**

Out-of-sample performance on the subset of clients for whom we optimize – 1.2 times the performance of the baseline

Interpretable Cross validation algorithm

Our algorithm consistently converges to models with better out of sample performance





1. Sample from initial grid space parameters values randomly
2. After n iterations, fit a linear model. Use the coefficients to define in which direction to move
3. Stochastically define new grid to be skewed toward the error reducing direction (in expectation)

Phase 3: Optimize Strategies

~13000 Advisors | **100 Strategies** | **2 Quarters**

We optimize interaction sequences for 6 months over the top client firm. We select the strategies that most frequently occur and validate them with domain experts

Optimization Formulation

$$\max_{s} \sum_{ij}\left(\sum_{t}^{2}\alpha_{ijt}\right)s_{ij} - \lambda\sum_{ij} m_j s_{ij} - \mu\sum_{ij} c_j s_{ij}$$

s.t	$\sum_{j=1}^{m} s_{ij} \leq 1$	$i \in [n]$
	$\sum_{ij} m_j s_{ij} ex_{iw} \leq 25 * 26$	$i \in [k]$
	$\sum_{ij} c_j s_{ij} in_{iw} \leq 50 * 26$	$i \in [k]$
	$s_{ij} \in \{0,1\}$	

s_{ij}	Recommend strategy j with advisor i
α_{ijt}	Predicted sales increase of s_{ij} in period t
c_j, m_j	Number of calls and meetings of strategy j
ex_{iw}, in_{iw}	Mapping of advisor i to wholesaler w
λ, μ	Cost of meetings and calls