Optimal Client Interaction

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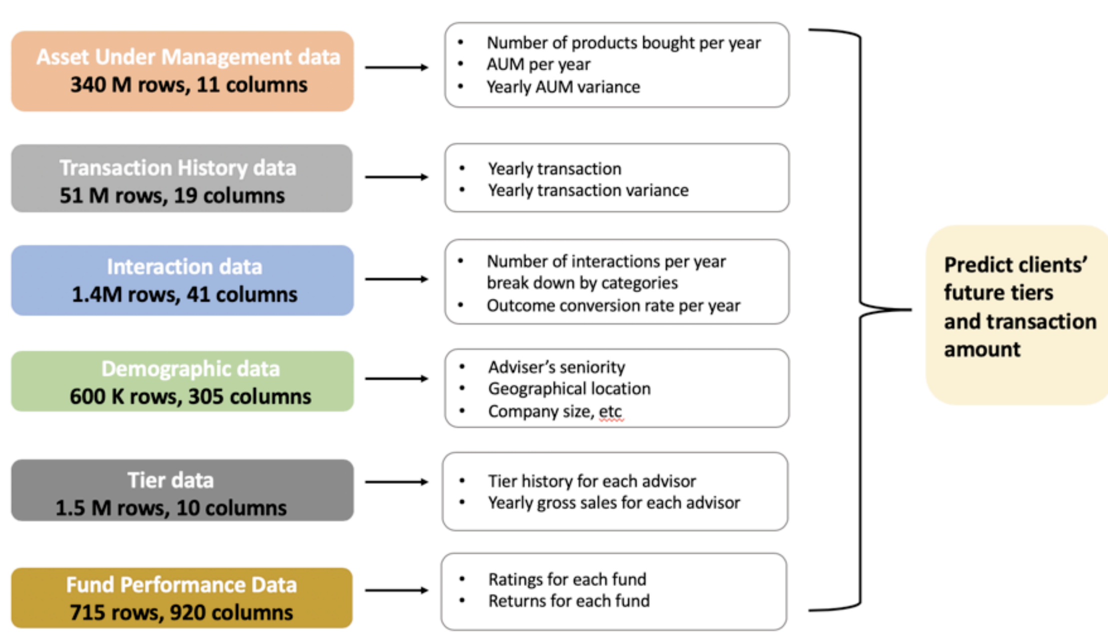
Project Overview

Problem Statement

Utilize analytical tools to extract insights from existing clients to better understand the prospects, particularly on:

- ➢ **WHO**: Which advisors to target
- ➢ **HOW**: How to spend our time with the advisors

Dataset Description



- ❖ The final master data frame contains 94,540 advisors with 91 features spanning from 2017 to 2019
- ❖ Top and bottom advisors have significantly different behaviors for asset under management and transaction
- ❖ Live calls and in-person meetings are the dominant types of interaction

Solution Plan

Step 1
- • Group advisors into Tier A – Tier D
- • Tier D advisors identified as prospects

Step 2
- • Predict future tiers and sales
- • Look for prospects with tier lift or significant sales lift

Step 3
- • Prescribe the optimal ways of interaction to each prospect

Timeline

March – April
Receive Data and Set up technical tools

May
Data processing and feature engineering

June
Build predictive model pipelines

July
Build prescriptive models

August
Final Deliverables

Methods

Prediction: Who to Target

Define the targets

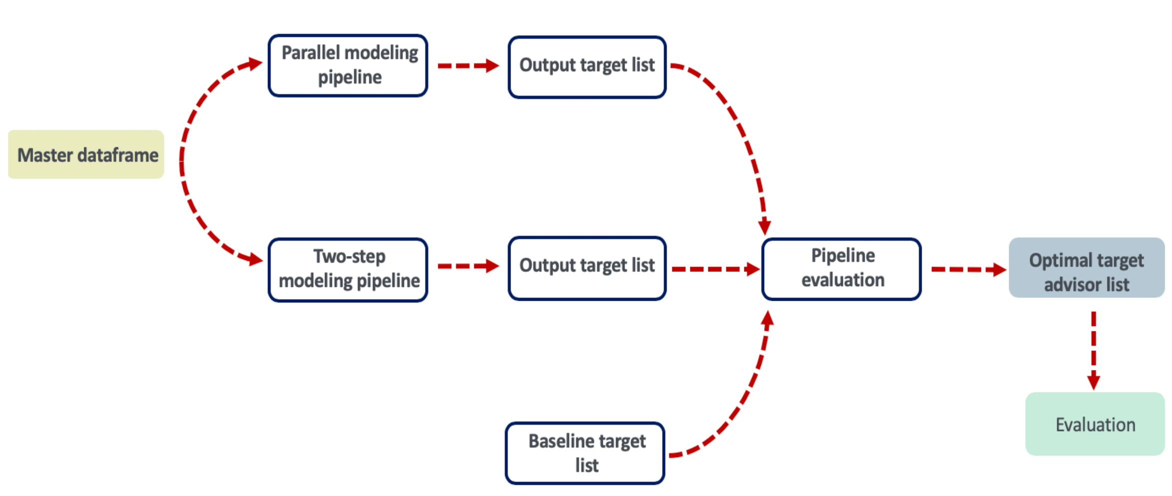
Target # 1
Advisors who tier up

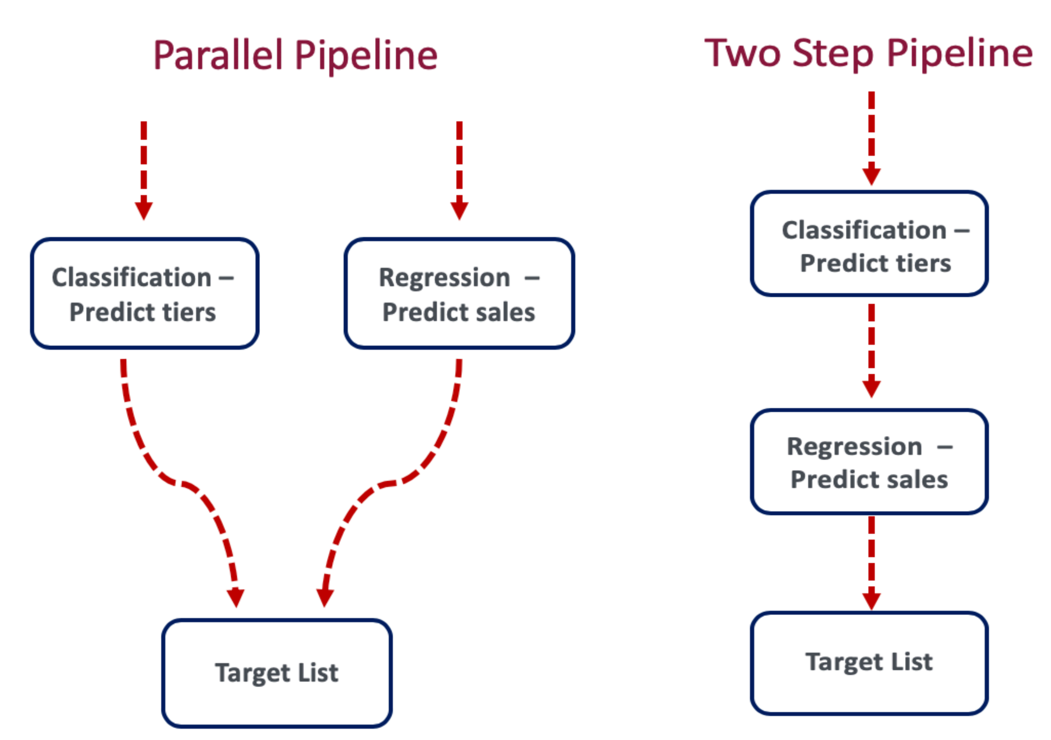
Target # 2
Advisors who have significant sales lift without tier-up

Classification:
- multi-class classification
  - Decision Tree
  - RandomForest
  - XGBoosting
  - Optimal Classification Tree
- hierarchical classification
  - Decision Tree
  - RandomForest
  - XGBoosing

Regression:
- Linear Regression
- Lasso
- Elastic Net
- Decision Tree Regressor
- RandomForest
- XGBoosting

Modeling Structure

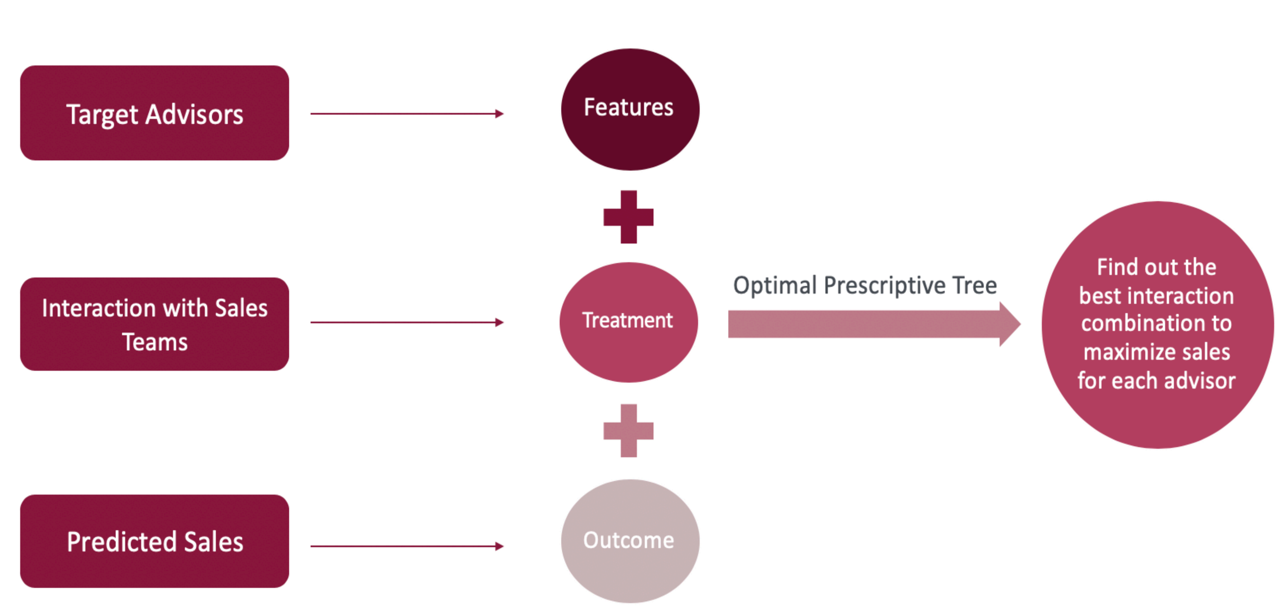


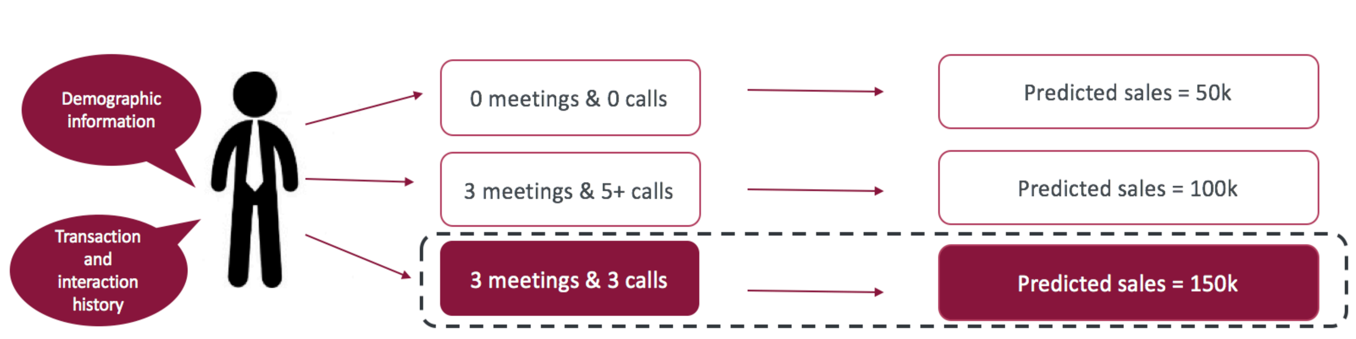


- ❖ The only difference between two pipelines is the way classification and regression models are combined

Prescription: How to Target

- ❖ Goal: Assign the optimal combination of calls and meetings to maximize sales on each financial advisor





Results & Conclusions

Predictive Model Evaluation

a) Evaluation on modeling pipelines

Classification

Feature	Number of Occurrence across Years
Gross Sales 1 year back	3
Tier 1 year back	3
Number of $100K product 1 year back	3
Gross Sales 2 year back	3
Tier 2 year back	2
Number of years at current firm	2

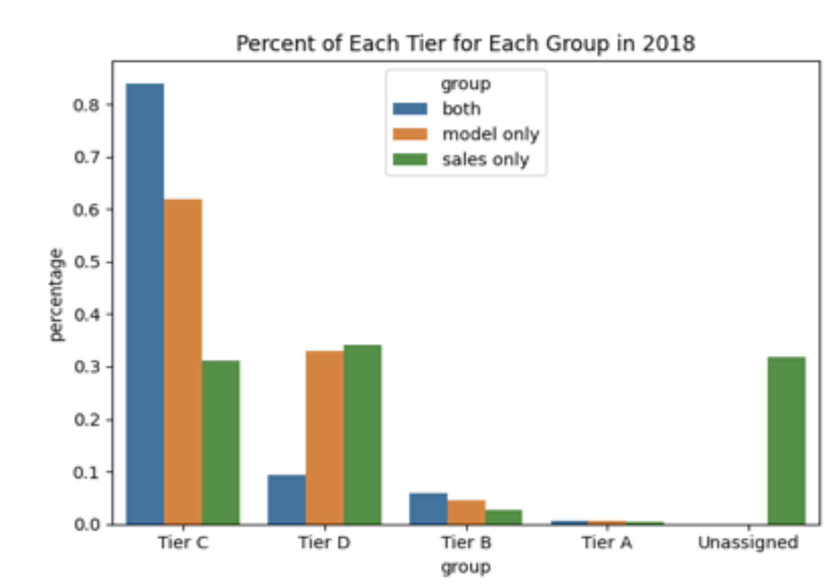
Regression

Feature	Number of Occurrence across Years
Years of business with MFS	3
Gross Sales 1 year back	3
Gross Sales 2 year back	3
Number of $100K product 1 year back	3
Years since an advisor became registered	3
Advisor's registration type	3
Tier 1 year back	2
Advisor's Title	2
If advisor is independent contractor	2

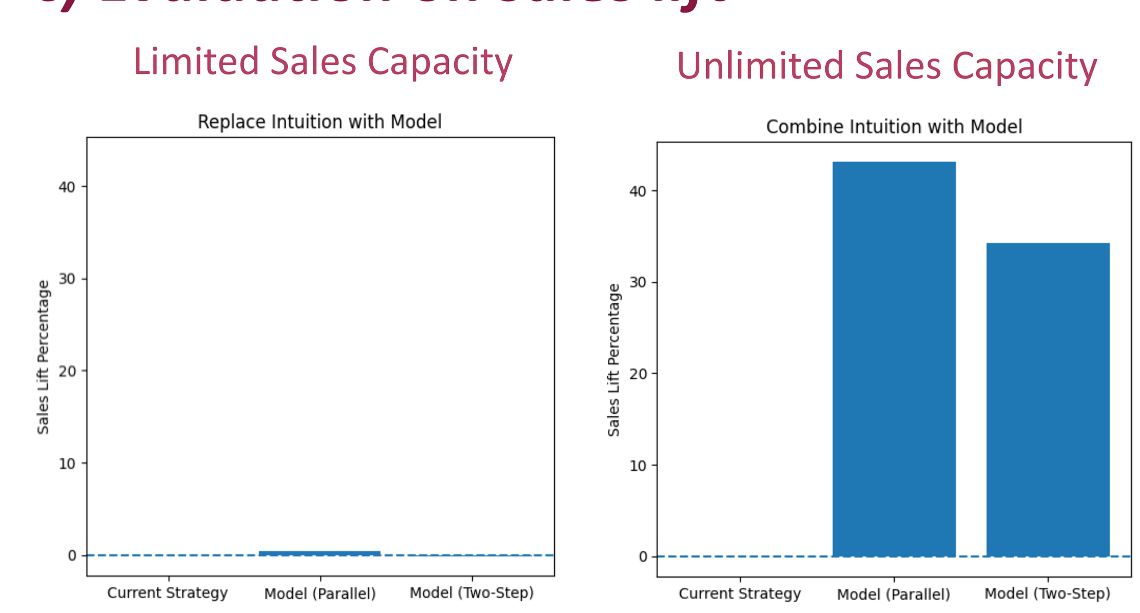
- ❖ We ran the models on 2017, 2018, and 2019
- ❖ The best classification models give out-of-sample accuracy scores consistently above 0.7
- ❖ The best regression models give out-of-sample R^2 ranging from 0.4 ~ 0.5

b) Evaluation on advisor growth

- ❖ There are ~ **30%** more advisors lifting up to higher tiers in the population selected by the models than those selected by the sales team in the second year



c) Evaluation on sales lift



- ❖ We can improve the total gross sales by **43.14%** with **~50%** more advisors identified

Prescriptive Model Evaluation

Method	Treatment accuracy	Outcome accuracy
OPT with Tuned prescription factor (optimal 0.6), stratified split	0.1	**-0.05**
Regress & Compare, LASSO	0.03	-1.9
Regress & Compare, kNN	**0.67**	-5.58

- ❖ OPT beats Regress & Compare methods by balancing outcome prediction and optimal treatment assignment

Recommendations

- ❖ Combining the predicted model with sales teams expertise gives the best targeting result
- ❖ For predicted model, we can tailor the model to firm level to achieve more specialized alignment strategy
- ❖ For prescriptive model, we can leverage a greater dataset and utilize Policy Trees to assign optimal dosages for both arms of our treatment