

# Personalized Client Offerings with Product Affinity Models

Studiengang Data Science (HS2021)

Daniel Perruchoud, Institut für Data Science



### Product Affinity Modeling





- Choose product in scope
- Determine eligible clients
- Collect clients who purchased product in the past
- Determine clients' characteristics before product purchase
- Select complementary clients without product purchase
- Compare buyer's vs non-buyers deriving discriminating client traits
- Use analytics insights to develop machine learning model
- Test model validity "in the lab" on unseen client data
- Explain and translate model results
- Define experimental design for marketing campaign
- Measure success of marketing campaign "in the wild" over time
- Deploy product affinity model into production



#### Choose product in scope...

- ... e.g. based on their revenue impact or loyalty impact.
- Note: successful product affinity models use the "behavioral cross selling" paradigm, i.e. we learn from the client's who already have one/several banking products and their interaction with the bank. This also requires successful product sales of a few 100x in the past. New client acquisition requires a different approach.

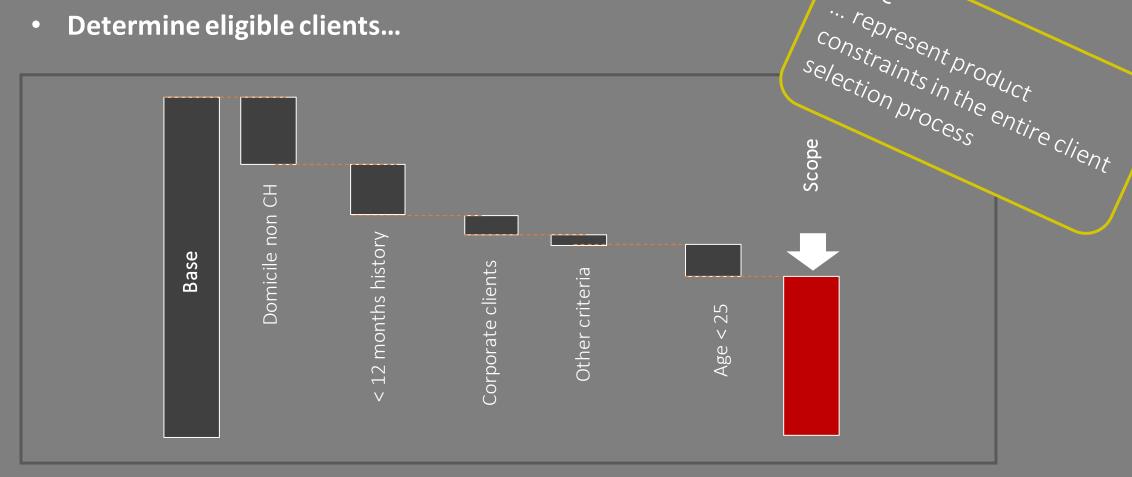
#### Determine eligible clients...

- ... based the products "legal restrictions", with respect to e.g. age or domicile restrictions.
- Note: these constraints need to be reflected in the client selection process. Also explicitly decide whether to focus on first-buyers vs repeat-buyers.

PRÄDIKTIVE MODELLE

Product Affinity Modeling – Steps towards an Analytical Proof of Concept

Determine eligible clients...





#### Collect clients who purchased product in the past...

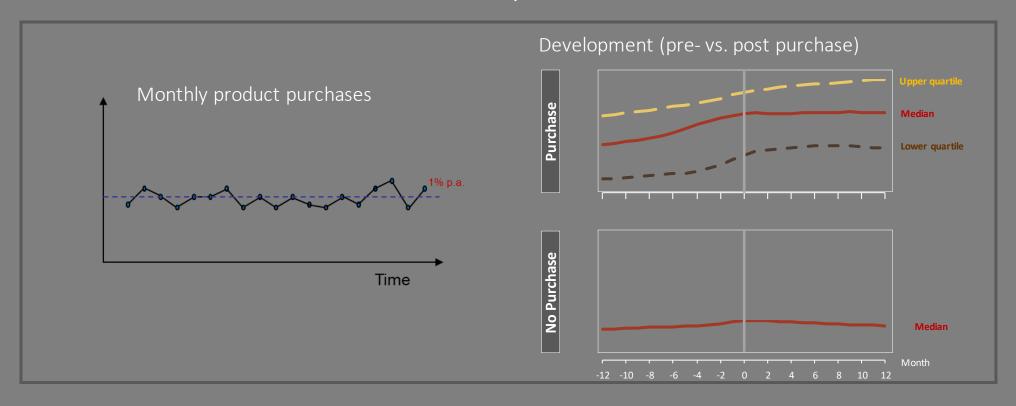
- ... by considering e.g. up to 3 years into the past.
- Note: the product's features and general competitive environment should be comparable to today's
  conditions. Collecting clients over several months has the benefit of increasing the number of clients to
  learn from and results in a model which can deal with seasonal patterns and be applied regularly. Make
  sure to analyze characteristics of these clients and if appropriate refine target client selection.

#### Select complementary clients without product purchase...

- ... by considering the same time period as above.
- Note: buyers and non-buyers of the product need to be exposed to the same external market conditions for obtaining a fair comparison and a generalizable model. Finding appropriate complementary clients required more thinking than selecting client who purchased a product!



- Collect clients who purchased product in the past...
  - across several months to stabilize model predictions and check their behavior





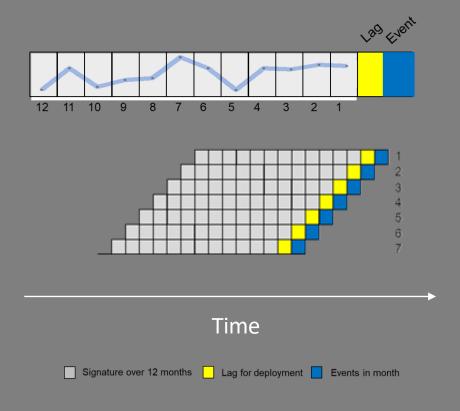
MODELLE



- Compare buyer's vs non-buyers deriving discriminating temporal client traits...
  - ... by using business knowledge and hand-crafted business analytical variables (BAV) & ML models.
  - Note: putative/potential purchase drivers are selected and organized into a client analytical record ("golden record"). To understand and communicate the impact of individual attributes univariate exploratory analysis conditioned on the target attribute can be useful. For predictive models representing the buyer's behavior before the product purchase is crucial!
- Use analytics insights to develop machine learning model...
  - ... by combining BAVs and applying best-in-breed model.
  - Note: model selection is guided by principles such as "performance", "flexibility", "scalability", "automation", "convenience", "robustness" and "explainability". Develop a simple base line model to proceed rapidly and gain confidence. Carefully analyze main drivers of the model before applying product affinity model.



- Compare buyer's vs non-buyers deriving discriminating temporal client traits...
  - Create **client analytical record**, i.e. one observation per client.
  - Roll-up pre-purchase client history to capture trends using 12 months to eliminate seasonal effects.
  - Use clients from multiple timeframes to stabilize model performance for regular model application.
  - Prepare data using lag or latency month before purchase to be able to model the client's decision to purchase (additionally data for scoring are typically delivered with delay).

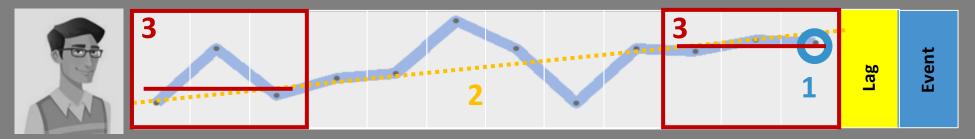






- Compare buyer's vs non-buyers deriving discriminating temporal client traits...
  - A fast and effective way is to represent time series by distributional parameters
  - Client behavior is reflected by temporal characteristics across multiple financial attributes...

One client, time series of single financial attribute



#### Distributional Parameters

Minimum Maximum Median Mean

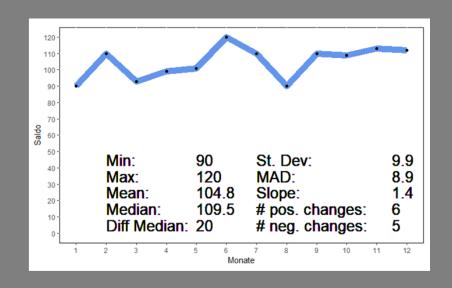
Situation before event Stand. deviation Median abs. deviation Median 1st vs last 3 months Linear trend Spearman correlation # positive 1<sup>st</sup> differences





- Compare buyer's vs non-buyers deriving discriminating temporal client traits...
  - Minimum, Maximum, Mean, Median
  - Slope, robust linear trend
  - Standard deviation, MAD, Change of Median
    - Min: 90 St. Dev: 8
      Max: 113 MAD: 11.9
      Mean: 102.2 Slope: 2.2
      Median: 101.5 # pos. changes: 9
      Diff Median: 20 # neg. changes: 2

- Number of positive / negative first\_differences
- Number of times above / below mean,
- Absolute sum of changes
- •



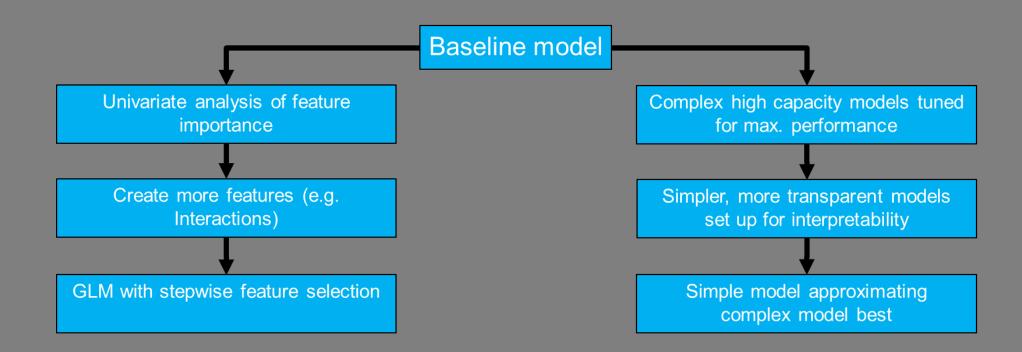




- Use analytics insights to develop machine learning model...
- Guiding principles
  - Performance: best-in-breed classifiers
  - Explainability: impact of individual attributes
  - Flexibility: easily integrating different types of data (nominal, ordinal and continuous attributes)
  - Robustness: robustness to noise and extreme values of attribute and applicability in presence of imbalanced classes
  - Convenience: low / moderate parameter tuning required
  - Scalability: fast on large data sets with modest hardware
  - Automation: no / low pre-preprocessing of attributes & missing values and automatic attribute selection
- Tree-based ensemble models like RandomForest, XGBoost, LightGBM or CatBoost
  - score fast, predict well, flexibly integrate different data types
  - are robust in production & easy to communicate



Use analytics insights to develop machine learning model...

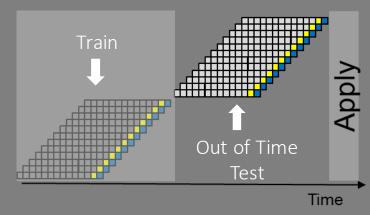


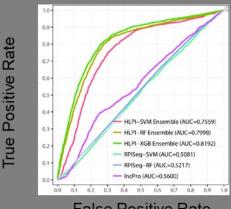


- Test model validity "in the lab" on unseen client data...
  - ... by using a train-test split and appropriate analytical metrics.
  - Note: independence of the data partitions "train", "validate", "test" is crucial to prevent data leakage, i.e. client information used for training the model needs to be excluded from the test data partition. The value-add of the model in particular for imbalanced datasets is best assessed via ROC curves (true positive rate vs false positive rate).
- Explain and translate model results...
  - ... by assessing the overall main drivers of a model.
  - Note: Identify main drivers on an individual client basis is the next step. Both assessments are useful
    for analytical experts and need considerable translation work to be understood by non-data scientist.



- Test model validity "in the lab" on unseen client data...
  - Partition your data set into train, validate and test set (several options possible), if possible train and test data periods differ
  - Develop your model on the train set, optimize your model with validation data, then assess your model with test data
  - Use metrics (e.g. precision, recall) which are not impacted by data imbalance
  - Assess and compare metrics across multiple candidate models

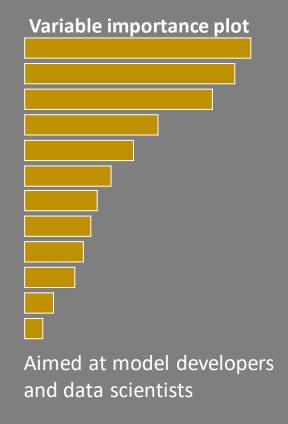




False Positive Rate



Explain and translate model results...







Aimed at investment specialists



#### • Define experimental design for marketing campaign...

- ... by balancing marketing budget vs expected client response.
- Note: product affinity models result in a client list ranked by their "propensity to buy". This list can be
   "harvested" based on the marketing budget or the sales force capacities available. Model selection
   impact can be assessed by comparing targeted top scorers with control group clients, campaign
   effectiveness can be assessed by comparing targeted top scorers with held out top scorers.

#### Measure success of marketing campaign "in the wild" over time...

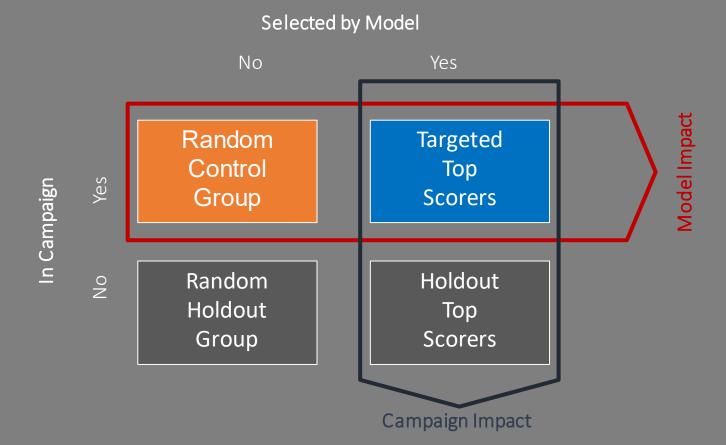
- ... by using a variety of business metrics, e.g. interest expressed, product purchased, product used, revenue generated.
- Note: different business metrics operate on different time scales.

#### Deploy product affinity model into production...

- ... by parametrizing model pipeline and developing a model monitor.
- Note: Model monitor requires inspection of temporal consistency of raw information, model input data and global attribute importance metrics, distribution and change of scores as well as client response measurement.



Define experimental design for marketing campaign...

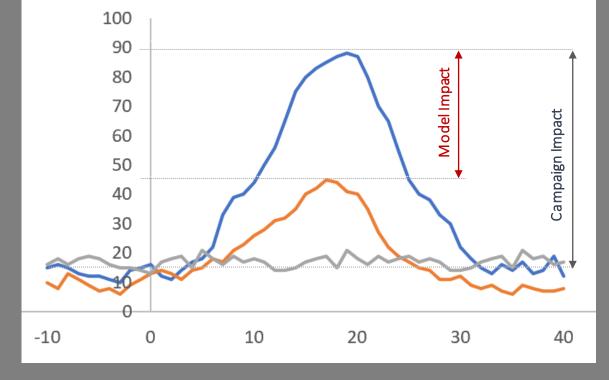






Measure success of marketing campaign "in the wild" over time

Sales



- Targeted Top Scorers
- Random Control Group
- Holdout Top Scorers