

## BI REPORTING CASE STUDY SUMMARY


| Project Name               |                             | Brief Description  | Key analyses  |
|----------------------------|-----------------------------|--|---|
| PROPENSITY TO PAY MODELING | COLLECTION SERVICES COMPANY | Partnered with the client to build a “ <b>propensity to pay</b> ” <b>model to help them identify high value accounts</b> , scientifically allocate agent resources to those accounts and enable the company to improve its Credit Collection Performance | <ul style="list-style-type: none"><li>• Poisson regression analysis</li></ul> |

# CASE STUDY: PREDICTIVE MODELING FOR A COLLECTION SERVICES COMPANY


## ABOUT THE CLIENT

### Propensity To Pay Modeling For A Collection Services Client


#### SITUATION

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- Company was a **regional debt collection agency** that worked on third-party consumer portfolios
  - The company **wanted to improve its credit collection performance** and **scientifically allocate its agent resources** to the high value account portfolios and customers
  - Merilytics partnered with the company **to build a “propensity to pay” model** that would rank the portfolios and customers within the portfolios, on a monthly basis
  - This propensity-to-pay ranking model would **enable the company to prioritize its resources** and work those accounts with higher intensity

#### VALUE ADDITION

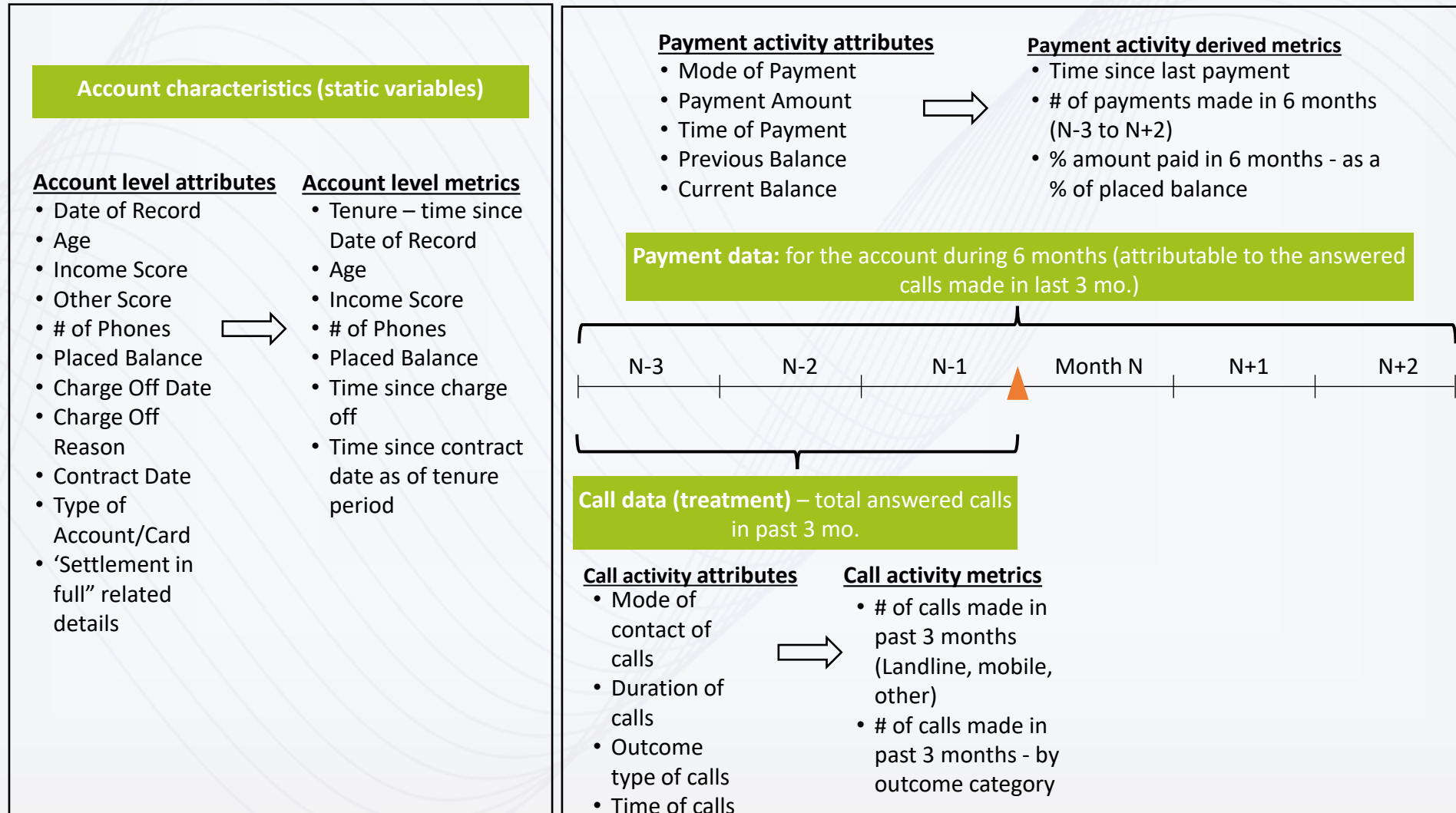
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- **Shortlisted accounts from the portfolio** for propensity to pay modeling, after factoring for data noise and shorter tenure
  - **Defined** a set of **independent variables** across account characteristics, payment data and ‘treatment’ data and **dependent variable** as ‘number of payments’
  - **Ran a “matching” algorithm** on historically treated (contact made by any person or machine) and non-treated account sets, to remove treatment bias
  - **Conducted a zero-inflated Poisson regression** analysis on the matched data set, and ranked accounts in descending order of payment likelihood

#### IMPACT

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- Critical **variables in determining the payment likelihood** were identified
  - Enabled the company to achieve a **~10% lift in payments**, and by treating fewer accounts

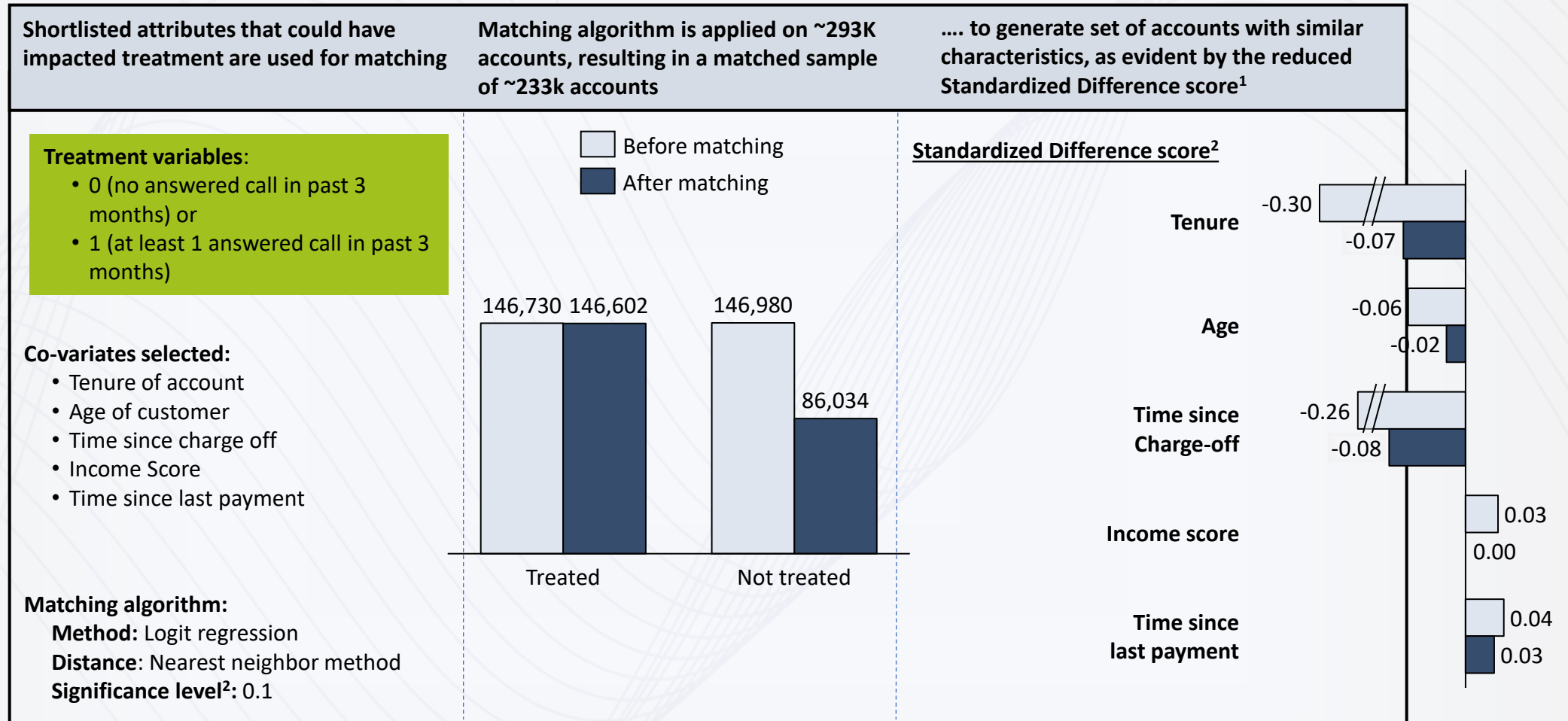
# DEFINED A SET OF INDEPENDENT VARIABLES ACROSS ACCOUNT CHARACTERISTICS, PAYMENTS AND 'TREATMENT' DATA AND DEPENDENT VARIABLE AS '# OF PAYMENTS'

Snapshot of information captured for an account with tenure 'N'<sup>1</sup>



<sup>1</sup> Tenure N represents 'N<sup>th</sup>' month of the account since the Date of Record

# 'MATCHING' OF ACCOUNTS WAS DONE TO REMOVE EFFECT OF 'TREATMENT' BIAS



<sup>1</sup> Standardized Difference signifies the extent of lack of overlap in distribution curves of the metric, between treated and non-treated sets of accounts

<sup>2</sup> Significance level indicates the extent of robustness of the predictive model for propensity to treat. E.g., significance level of 0.10 indicates there that there is less than 10% probability that the results from the regression are not representative of the true relationship between covariates and dependent variable



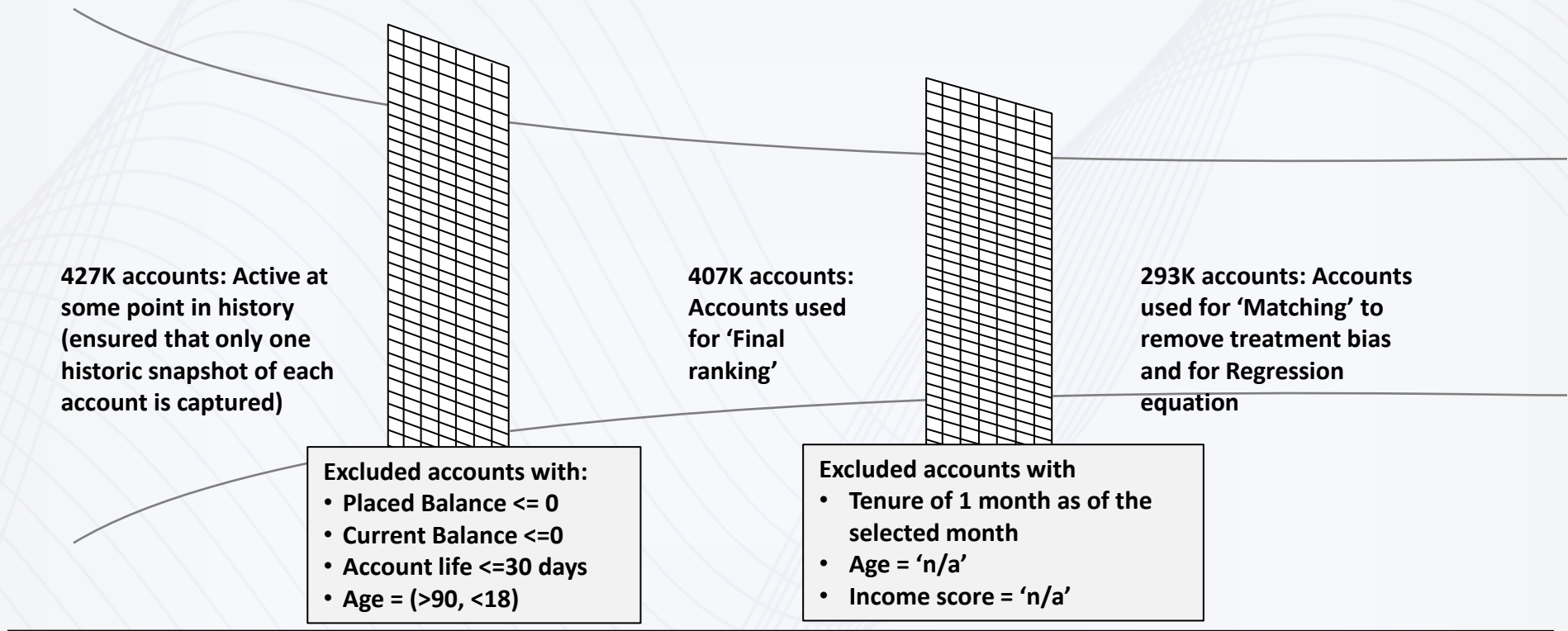
# ZERO INFLATED POISSON REGRESSION<sup>1</sup> WAS RUN ON THE MATCHED ACCOUNTS TO DEVELOP A PROPENSITY MODEL THAT WAS USED TO RANK ALL ACCOUNTS

| Selected attributes that affect the propensity to pay, defined the dependent variable...  | ...ran 'Zero-inflated Poisson regression model' on the matched sample of accounts - 233K  | ...generated the ranking of accounts by applying the model on 407K accounts   |
|---|---|---|
| <div><b>Dependent Variable</b><ul style="list-style-type: none"><li># of payments made in 6 months (N-3 to N+2 months)</li></ul></div> <div><b>Independent Co-variables:</b><ul style="list-style-type: none"><li><b>Account Level Attributes</b><ul style="list-style-type: none"><li>Tenure</li><li>Age of customer</li><li>Income Score</li><li>Number of phone numbers</li><li>Time since charge-off</li></ul></li><li><b>Call Activity Attributes:</b> # of successful calls made in past 3 months</li><li><b>Payment Activity Attributes:</b> Time since last payment</li><li><b>Matching Attribute:</b> Derived P-score<sup>1</sup> from matching step</li></ul></div> | <div><b>Regression on matched sample of data</b><ul style="list-style-type: none"><li>Matched sample of accounts – 232,636</li><li><b>% of accounts that made zero payments in 6 month period – 95.58%</b></li><li><b>Regression technique: Two stage – zero inflated model</b><ul style="list-style-type: none"><li>Binomial with logit link – Predicts whether a person is likely to pay or not</li><li>Poisson with log link – Predicts the number of payments that a person is likely to make</li></ul></li><li><b>Significance level cut-off<sup>2</sup>:</b> 0.05</li></ul></div> | <ul style="list-style-type: none"><li>Applied regression model on 407K accounts to predict number of payments</li><li>Accounts are ranked based on the estimated likelihood of number of payments over a 6 month period</li></ul> <div><i>Rank 1</i><br/><i>Rank 2</i><br/><i>Rank 3</i><br/><i>.</i><br/><i>.</i><br/><i>.</i><br/><i>.</i><br/><i>.</i><br/><i>.</i></div> <div><i>Rank 407,335</i></div> |

1 P-score is the outcome variable in the matching step (Step 1) and signifies the propensity to treat (i.e., being contacted and answered by a person or machine)  
2 Significance level indicates the extent of robustness of the predictive model. E.g., significance level of 0.05 indicates there that there is less than 5% probability that the results from the predictive model are not representative of the true relationship between covariates and dependent variable

# ACCOUNTS FROM THE PORTFOLIO WERE SHORTLISTED ACCOUNTING FOR DATA NOISE AND SHORTER TENURE

Account funnel for the portfolio:



## Reasoning

- Negative/zero placed or current balance indicates data noise
- If total account life is  $\leq 30$  days, there is not enough treatment history
- For each snapshot, if current tenure is too low, we would not have sufficient history to run the matching algorithm, for that snapshot, for that account
- Missing age and income attributes could distort the matching model