Customer Retail Attrition – XAI Model

Solution Document

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1. Introduction

A Temenos AI predictive attrition model allows financial institutions to determine which active customers are likely to churn during the prediction time horizon - usually 3 months, based on the past behaviour of both the individual and the broader portfolio of customers.

Different account types have been assigned to two distinct broad categories: cash accounts and investment accounts.

The ability to predict customer attrition (churn) is an important part of any company management. The key point is that new customers are expensive to acquire and generally generate less revenue in the near term than established customers. After the initial period of exponential growth of the business has been left behind, churn modelling could be successfully applied to focus the retention efforts on high risk customers who might leave without the extra incentive.

Temenos AI leverages the intrinsically explainable nature of rules-based fuzzy models. Unlike opaque "black box" models such as neural networks, this approach to machine learning results in predictions that may be justified to a human being.

The models identify behaviour associated with disengagement, such as less deposits, less transactions, less products, which eventually lead to attrition. This disengagement happens over a period of a few weeks to a few months and can express itself in increasing/decreasing the values of total balances, number of products, transactions, credit transactions, pre-authorized debit transactions, i.e. recurring expenses, customer initiated debit transactions, i.e. day-to-day expenses, and so on.

The model gives explainable outputs at the level of full population (model rule base), sub-population groups exhibiting similar behaviour (Rules applicable to individual churn risk buckets) and single customers (interpretable rules/drivers based output for each customer). In addition to being completely transparent – the Temenos AI platform offers easy deployment and real time monitoring of the model performance.

- The Temenos approach provides centrally created support for decision makers at the front line, using Explainable AI (XAI). This approach has been successfully proven in numerous well known UK financial companies and can provide speedy augmentation of the decision making processes already in place.
- Temenos deploys the system, in the Cloud or On-premise, and works with the bank to fine-tune existing, proven, attrition models in short timescales of days or weeks as per requirements.
- The XAI models can be used via a web-interface for the end users or the models can be integrated in the bank's platform as the inferences are exposed via API calls.
- The XAI models allow the bank to add new input features (considerations) to the existing model.
- XAI widgets enable the evaluation of impacts of additional terms and conditions on attrition.
- Additional terms and conditions can be suggested for each individual decision by the profiling of the various customer segments extracted from the XAI bucketing tools.
- Decisions can optionally be saved onto the XAI platform for future reference by tagging individual predictions with a customer ID

- Temenos XAI can monitor and analyse your population using XAI analytics dashboards for population and characteristic classification. This allows the user to monitor and change the rules and policies based on changes observed in the overall customer characteristics.
- Temenos XAI can provide actionable insights, and identify new approaches that are working, and provide feedback through an inference webpage to test different approaches for a given customer.
- Customers can be ranked according to their churn probability to prioritise which ones the bank should reach out to, in order to increase the likelihood of retention
- Periodic reviews using actual attrition outcomes for the customers processed through the XAI models can give insights into the effectiveness of any existing retention strategy. This can then serve as an input into generating better models going forward.

2. Business Requirements Met by the Solution

- The model can be adapted to work with any data source, if they can provide data to derive the model features.
- By default the model integrates the Temenos XAI platform with Temenos Data Warehouse and Temenos Analytics Platform for an end-to-end solution; however banks may also utilise the attrition model on the XAI platform as a standalone solution.
- For every valid inference, the model gives an output between 0 to 1 (both inclusive), where scores closer to 0 indicate a low churn risk and scores closer to 1 indicate a high churn risk. These scores are also mapped to a probability of attrition.
- The scores generated by the model have a monotonic meaning – i.e. a score of 0.8 cannot signify a lower probability of default than a score of 0.79 – and the same is true for all numbers between 0 and 1.
- The model output includes an ‘explanation’ in form of drivers and the rules behind every individual prediction.
- The model has a transparent global rule base for arriving at individual customer attrition scores.
- The model supports changes in form of addition/modifications/deletions to its rule base conditional on the modifications involving valid input values.
- The model supports examining the changes in scores arising from a change to any/all the input value/s.
- The model supports storing of scores and inputs for all historical inferences.
- The model supports investigating distribution of scores from a ‘Live’ population against the original population used to build the model
- The model supports adding extra information/features via new/amended rules and generating an updated model to consider new information that was not available historically
- The model supports one-click deployment on the cloud.
- A churn risk bucket analysis can be carried out on a population with known outcomes (Bucketing)

- The bucketing allows for customization on number of buckets
- The bucketing allows for ‘goal-seek’ analysis on buckets in terms of number of minority class instance in each bucket
- The bucketing allows for ‘goal-seek’ analysis on buckets in terms of percentage of minority class instance in each bucket

3. Current Functionality

There is no existing functionality within the Temenos product suite offering similar functionality/scope. At the customer end, existing functionality is specific to each bank, if any such framework exists at all.

4. The Solution

4.1 Overview

The trained model provides responses using an API call with a unique model key for each deployment of the model. The model is called with selected variables from either Temenos Data Warehouse or an alternative datasource provided by the client – these are then passed through a pre-processing pipeline which prepares the final features for the model and sends the same to the model inference engine. The model response is then fed back to the caller. The process is described in detail in the next section.

4.2 Run Time

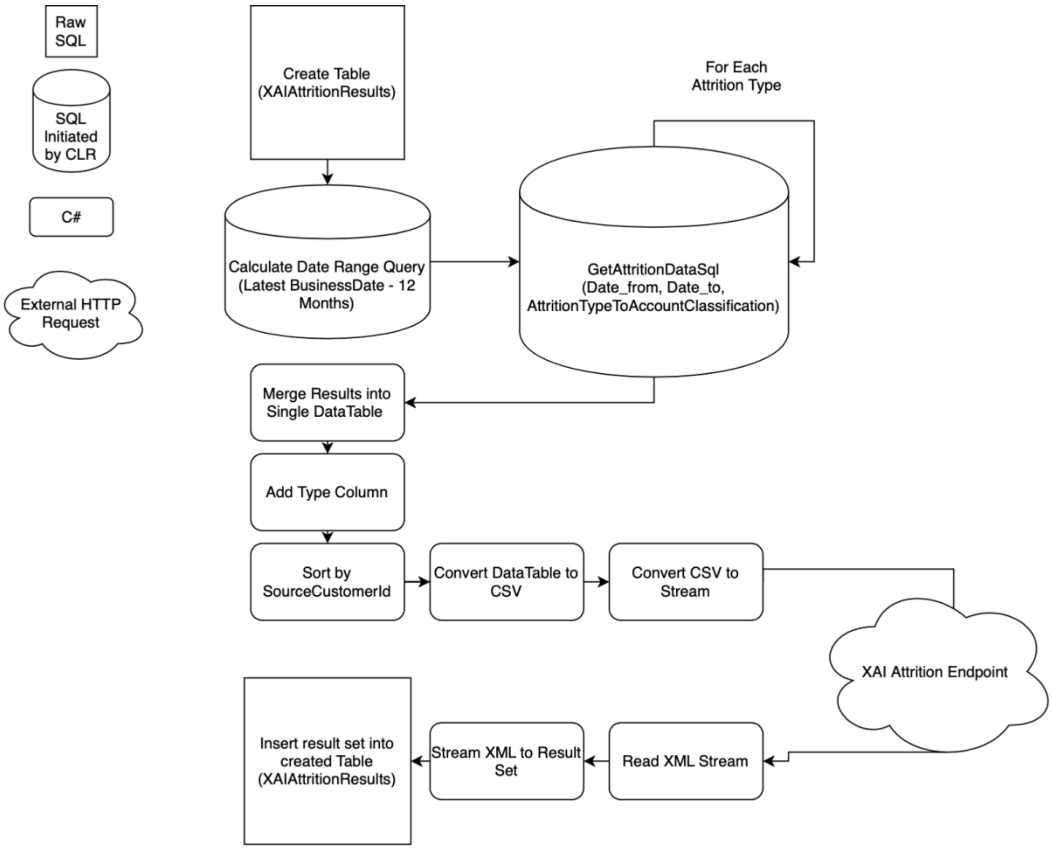

Figure 1: Typical Model Runtime Flow

Error! Reference source not found. shows an overview of the model runtime flow, if the bank is using the pre-built solution that integrates the Temenos XAI platform with Temenos Data Warehouse and Temenos Analytics Platform. At run time the request containing the 'raw information' from the data warehouse and other optional information hits the XAI endpoint. The XAI endpoint performs further processing to derive the feature set that is used to obtain inferences from the model. Some post-processing is applied to the model JSON response which is then streamed back to Analytics Platform as XML.

If a client wishes to utilise the XAI platform as a standalone solution, independent of the data warehouse and/or the Analytics Platform, the model runtime flow will change accordingly. The client must have a data source from which either they derive the exact fields used by the model, or Temenos XAI may otherwise implement a custom preprocessing layer to transform client inputs into model features; either way the bank will simply hit the attrition endpoint which will be configured accordingly. The structure of the response they receive may then also be modified, e.g. if the client would prefer JSON to be streamed back rather than XML.

Table 1 shows a feature set used for an Attrition model. This is a subset of the full available feature set, which is listed below the table. Details on the definitions and derivations of each feature may be viewed in the Attrition User Guide, under Data Requirements. If a bank generates a project on the XAI platform with its own data, i.e. to generate a bespoke model rather use than a pre-built attrition model provided by Temenos, then they will be able to select the most predictive subset of features from the full set using the XAI Platform's feature selection functionality. As per the table, a feature set of size in the range 30-50 features is typically best.

raw	alias
CASH_AvgBalance_Current	Average Balance from Cash Accounts this Month
CASH_average_debit_trxn_value	Average Debit Transaction Value from Cash Accounts this Month
CASH_average_credit_trxn_value	Average Credit Transaction Value from Cash Accounts this Month
CASH_average_trxn_value	Average Transaction Value from Cash Accounts this Month
CASH_avg_monthly_num_credit_trxns_last_3m	Avg Monthly Number of Credit Transactions last 3M from Cash Accounts
CASH_min_monthly_num_credit_trxns_last_3m	Min Monthly Number of Credit Transactions last 3M from Cash Accounts
CASH_min_monthly_num_credit_trxns_last_6m	Min Monthly Number of Credit Transactions last 6M from Cash Accounts
CASH_max_monthly_num_credit_trxns_last_9m	Max Monthly Number of Credit Transactions last 9M from Cash Accounts
CASH_min_monthly_num_credit_trxns_last_9m	Min Monthly Num Credit Transactions last 9M from Cash Accounts
CASH_avg_num_monthly_trxns_last_12m	Avg Num Monthly Transactions last 12M from Cash Accounts
CASH_avg_num_monthly_debit_trxns_last_12m	Avg Num Monthly Debit Transactions last 12M from Cash Accounts
CASH_avg_monthly_num_credit_trxns_last_12m	Avg Monthly Num Credit Transactions last 12M from Cash Accounts
CASH_max_monthly_num_credit_trxns_last_12m	Max Monthly Num Credit Transactions last 12M from Cash Accounts
CASH_min_monthly_num_credit_trxns_last_12m	Min Monthly Num Credit Transactions last 12M from Cash Accounts
CASH_ratio_num_trxns_1m	Ratio Number of Transactions Current to 1M ago in Cash Accounts
CASH_ratio_num_trxns_9m	Ratio Number Transactions Current to 9M ago in Cash Accounts

INVESTMENT_CountDebitAmount_Current	Number of Debit Transactions this Month from Investment Accounts
INVESTMENT_SumCreditAmount_Current	Value of Credit Transactions this Month from Investment Accounts
INVESTMENT_average_credit_trxn_value	Average Credit Transaction Value from Investment Accounts
INVESTMENT_max_num_monthly_debit_trxns_last_3m	Max Number of Monthly Debit Transactions last 3M from Investment Accounts
INVESTMENT_avg_monthly_debit_trxn_value_last_3m	Avg Monthly Debit Transaction Value last 3M from Investment Accounts
INVESTMENT_avg_monthly_num_credit_trxns_last_3m	Avg Monthly Number of Credit Transactions last 3M from Investment Accounts
INVESTMENT_min_monthly_num_credit_trxns_last_3m	Min Monthly Number of Credit Transactions last 3M from Investment Accounts
INVESTMENT_avg_monthly_credit_trxn_value_last_3m	Avg Monthly Credit Value Transactions last 3M from Investment Accounts
INVESTMENT_min_monthly_credit_trxn_value_last_3m	Min Monthly Credit Transaction Value last 3M from Investment Accounts
INVESTMENT_max_num_monthly_trxns_last_6m	Max Number of Monthly Transactions last 6M from Investment Accounts
INVESTMENT_min_num_monthly_debit_trxns_last_6m	Min Number of Monthly Debit Transactions last 6M from Investment Accounts
INVESTMENT_max_monthly_num_credit_trxns_last_6m	Max Monthly Number of Credit Transactions last 6M from Investment Accounts
INVESTMENT_min_monthly_num_credit_trxns_last_6m	Min Monthly Number of Credit Transactions last 6M from Investment Accounts
INVESTMENT_avg_monthly_num_credit_trxns_last_9m	Avg Monthly Number of Credit Transactions last 9M from Investment Accounts
INVESTMENT_min_monthly_num_credit_trxns_last_9m	Min Monthly Number of Credit Transactions last 9M from Investment Accounts
INVESTMENT_min_monthly_trxn_value_last_12m	Min Monthly Transaction Value last 12M from Investment Accounts
INVESTMENT_avg_monthly_credit_trxn_value_last_12m	Avg Monthly Credit Transaction Value last 12M in Investment Accounts

INVESTMENT_ratio_AvgBalance_9m	Ratio Avg Balance this Month to 9M ago in Investment Accounts
Age	Customer Age
HasCurrent_Account_Current	Has Current Account
HasSavings_Current	Has Savings Account
HasTerm_Deposit_Current	Has Term Deposit
HasLeasing_Current	Has Leasing Account
HasMortgage_Current	Has Mortgage
HasRevolving_Credit_Current	Has Revolving Credit
HasTerm_Loan_Current	Has Term Loan
DepsBalance_Current	Deposit Balance this month
diff_NumProducts_1m	Difference in products in the last month
diff_NumProducts_9m	Difference in products in the last 9M

Table 1 Example Feature Set; Raw Names And Aliases

The full list of potential modelling features is:

Age

CASH_AvgBalance_Current

CASH_CountCreditAmount_Current

CASH_CountDebitAmount_Current

CASH_SumCreditAmount_Current

CASH_SumDebitAmount_Current

CASH_average_credit_trxn_value

CASH_average_debit_trxn_value

CASH_average_trxn_value

CASH_avg_monthly_credit_trxn_value_last_12m

CASH_avg_monthly_credit_trxn_value_last_3m

CASH_avg_monthly_credit_trxn_value_last_6m

CASH_avg_monthly_credit_trxn_value_last_9m

CASH_avg_monthly_debit_trxn_value_last_12m

CASH_avg_monthly_debit_trxn_value_last_3m

CASH_avg_monthly_debit_trxn_value_last_6m

CASH_avg_monthly_debit_trxn_value_last_9m

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CASH_avg_monthly_num_credit_trxns_last_3m

CASH_avg_monthly_num_credit_trxns_last_6m

CASH_avg_monthly_num_credit_trxns_last_9m

CASH_avg_monthly_trxn_value_last_12m

CASH_avg_monthly_trxn_value_last_3m

CASH_avg_monthly_trxn_value_last_6m

CASH_avg_monthly_trxn_value_last_9m

CASH_avg_num_monthly_debit_trxns_last_12m

CASH_avg_num_monthly_debit_trxns_last_3m

CASH_avg_num_monthly_debit_trxns_last_6m

CASH_avg_num_monthly_debit_trxns_last_9m

CASH_avg_num_monthly_trxns_last_12m

CASH_avg_num_monthly_trxns_last_3m

CASH_avg_num_monthly_trxns_last_6m

CASH_avg_num_monthly_trxns_last_9m

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CASH_max_monthly_credit_trxn_value_last_3m

CASH_max_monthly_credit_trxn_value_last_6m

CASH_max_monthly_credit_trxn_value_last_9m

CASH_max_monthly_debit_trxn_value_last_12m

CASH_max_monthly_debit_trxn_value_last_3m

CASH_max_monthly_debit_trxn_value_last_6m

CASH_max_monthly_debit_trxn_value_last_9m

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CASH_max_monthly_num_credit_trxns_last_3m

CASH_max_monthly_num_credit_trxns_last_6m

CASH_max_monthly_num_credit_trxns_last_9m

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CASH_max_monthly_trxn_value_last_3m

CASH_max_monthly_trxn_value_last_6m

CASH_max_monthly_trxn_value_last_9m

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CASH_max_num_monthly_debit_trxns_last_3m

CASH_max_num_monthly_debit_trxns_last_6m

CASH_max_num_monthly_debit_trxns_last_9m

CASH_max_num_monthly_trxns_last_12m

CASH_max_num_monthly_trxns_last_3m

CASH_max_num_monthly_trxns_last_6m

CASH_max_num_monthly_trxns_last_9m

CASH_min_monthly_credit_trxn_value_last_12m

CASH_min_monthly_credit_trxn_value_last_3m

CASH_min_monthly_credit_trxn_value_last_6m

CASH_min_monthly_credit_trxn_value_last_9m

CASH_min_monthly_debit_trxn_value_last_12m

CASH_min_monthly_debit_trxn_value_last_3m

CASH_min_monthly_debit_trxn_value_last_6m

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CASH_min_monthly_num_credit_trxns_last_9m

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CASH_min_monthly_trxn_value_last_3m

CASH_min_monthly_trxn_value_last_6m

CASH_min_monthly_trxn_value_last_9m

CASH_min_num_monthly_debit_trxns_last_12m

CASH_min_num_monthly_debit_trxns_last_3m

CASH_min_num_monthly_debit_trxns_last_6m

CASH_min_num_monthly_debit_trxns_last_9m

CASH_min_num_monthly_trxns_last_12m

CASH_min_num_monthly_trxns_last_3m

CASH_min_num_monthly_trxns_last_6m

CASH_min_num_monthly_trxns_last_9m

CASH_num_trxns

CASH_ratio_AvgBalance_12m

CASH_ratio_AvgBalance_1m

CASH_ratio_AvgBalance_3m

CASH_ratio_AvgBalance_6m

CASH_ratio_AvgBalance_9m

CASH_ratio_num_trxns_12m

CASH_ratio_num_trxns_1m

CASH_ratio_num_trxns_3m

CASH_ratio_num_trxns_6m

CASH_ratio_num_trxns_9m

CASH_total_trxn_value

DepsBalance_Current

HasCurrent_Account_Current

HasLeasing_Current

HasLetter_of_Credit_Current

HasMortgage_Current

HasRevolving_Credit_Current

HasSavings_Current

HasTerm_Deposit_Current

HasTerm_Loan_Current

HasTrust_Current

INVESTMENT_AvgBalance_Current

INVESTMENT_CountCreditAmount_Current

INVESTMENT_CountDebitAmount_Current

INVESTMENT_SumCreditAmount_Current

INVESTMENT_SumDebitAmount_Current

INVESTMENT_average_credit_trxn_value

INVESTMENT_average_debit_trxn_value

INVESTMENT_average_trxn_value

INVESTMENT_avg_monthly_credit_trxn_value_last_12m

INVESTMENT_avg_monthly_credit_trxn_value_last_3m

INVESTMENT_avg_monthly_credit_trxn_value_last_6m

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INVESTMENT_avg_monthly_debit_trxn_value_last_3m

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INVESTMENT_max_monthly_debit_trxn_value_last_3m

INVESTMENT_max_monthly_debit_trxn_value_last_6m

INVESTMENT_max_monthly_debit_trxn_value_last_9m

INVESTMENT_max_monthly_num_credit_trxns_last_12m

INVESTMENT_max_monthly_num_credit_trxns_last_3m

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INVESTMENT_max_monthly_num_credit_trxns_last_9m

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INVESTMENT_max_monthly_trxn_value_last_3m

INVESTMENT_max_monthly_trxn_value_last_6m

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INVESTMENT_max_num_monthly_debit_trxns_last_3m

INVESTMENT_max_num_monthly_debit_trxns_last_6m

INVESTMENT_max_num_monthly_debit_trxns_last_9m

INVESTMENT_max_num_monthly_trxns_last_12m

INVESTMENT_max_num_monthly_trxns_last_3m

INVESTMENT_max_num_monthly_trxns_last_6m

INVESTMENT_max_num_monthly_trxns_last_9m

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INVESTMENT_min_monthly_credit_trxn_value_last_3m

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INVESTMENT_min_monthly_debit_trxn_value_last_3m

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INVESTMENT_min_monthly_debit_trxn_value_last_9m

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INVESTMENT_min_monthly_num_credit_trxns_last_3m

INVESTMENT_min_monthly_num_credit_trxns_last_6m

INVESTMENT_min_monthly_num_credit_trxns_last_9m

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INVESTMENT_min_num_monthly_debit_trxns_last_9m

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INVESTMENT_min_num_monthly_trxns_last_3m

INVESTMENT_min_num_monthly_trxns_last_6m

INVESTMENT_min_num_monthly_trxns_last_9m

INVESTMENT_num_trxns

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INVESTMENT_ratio_AvgBalance_1m

INVESTMENT_ratio_AvgBalance_3m

INVESTMENT_ratio_AvgBalance_6m

INVESTMENT_ratio_AvgBalance_9m

INVESTMENT_ratio_num_trxns_12m

INVESTMENT_ratio_num_trxns_1m

INVESTMENT_ratio_num_trxns_3m

INVESTMENT_ratio_num_trxns_6m

INVESTMENT_ratio_num_trxns_9m

INVESTMENT_total_trxn_value

LoanBalance_Current

NumAccounts_Current

NumProducts_Current

TotalBalance_Current

diff_NumAccounts_12m

diff_NumAccounts_1m

diff_NumAccounts_3m

diff_NumAccounts_6m

diff_NumAccounts_9m

diff_NumProducts_12m

diff_NumProducts_1m

diff_NumProducts_3m

diff_NumProducts_6m

diff_NumProducts_9m

API Request Structure:

The API can be interacted with using a JSON payload, which will include a Model Key. A sample payload for a single inference is shown below:


```
{
  "data": {
    "CASH_AvgBalance_Current": 0,
    "CASH_average_debit_trxn_value": 0.01,
    "CASH_average_credit_trxn_value": 0.01,
    "CASH_average_trxn_value": 0.01,
    "CASH_avg_monthly_num_credit_trxns_last_3m": 0,
    "CASH_min_monthly_num_credit_trxns_last_3m": 0,
    "CASH_min_monthly_num_credit_trxns_last_6m": 0,
    "CASH_max_monthly_num_credit_trxns_last_9m": 0,
    "CASH_min_monthly_num_credit_trxns_last_9m": 0,
    "CASH_avg_num_monthly_trxns_last_12m": 0,
    "CASH_avg_num_monthly_debit_trxns_last_12m": 0,
    "CASH_avg_monthly_num_credit_trxns_last_12m": 0,
    "CASH_max_monthly_num_credit_trxns_last_12m": 0,
    "CASH_min_monthly_num_credit_trxns_last_12m": 0,
    "CASH_ratio_num_trxns_1m": 0,
    "CASH_ratio_num_trxns_9m": 0,
    "INVESTMENT_CountDebitAmount_Current": 0,
    "INVESTMENT_SumCreditAmount_Current": 0,
```

```
    "INVESTMENT_average_credit_trxn_value": 0.01,
    "INVESTMENT_max_num_monthly_debit_trxns_last_3m": 0,
    "INVESTMENT_avg_monthly_debit_trxn_value_last_3m": -0.01,
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    "INVESTMENT_min_monthly_num_credit_trxns_last_3m": 0,
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    "INVESTMENT_min_monthly_credit_trxn_value_last_3m": 0,
    "INVESTMENT_max_num_monthly_trxns_last_6m": 0,
    "INVESTMENT_min_num_monthly_debit_trxns_last_6m": 0,
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    "INVESTMENT_min_monthly_num_credit_trxns_last_6m": 0,
    "INVESTMENT_avg_monthly_num_credit_trxns_last_9m": 0,
    "INVESTMENT_min_monthly_num_credit_trxns_last_9m": 0,
    "INVESTMENT_min_monthly_trxn_value_last_12m": -0.01,
    "INVESTMENT_avg_monthly_credit_trxn_value_last_12m": 0,
    "INVESTMENT_ratio_AvgBalance_9m": 0,
    "Age": 0,
    "HasCurrent_Account_Current": "Yes",
    "HasSavings_Current": "Yes",
    "HasTerm_Deposit_Current": "Yes",
    "HasRevolving_Credit_Current": "No",
    "HasTerm_Loan_Current": "No",
    "HasMortgage_Current": "No",
    "HasLeasing_Current": "No",
    "DepsBalance_Current": 0,
    "diff_NumProducts_1m": -5,
    "diff_NumProducts_9m": -7,
    "LG_EXTERNAL_ID": "Customer_123"
  },
  "modelKey": "abc-123-456-789-def",
  "detailed": "false",
  "dataSource": "live",
  "probability": true
}
```


The “detailed” flag controls the level of information returned by the response. If set to “true”, information on all triggered rules and their associated weights are returned. This option is useful in case the API response needs to be consumed in a bespoke UI layer.

The model also supports batch inference and a sample batch request payload is shown below:


```
{
 "batch": [{
  "CASH_AvgBalance_Current": 0,
  "CASH_average_debit_trxn_value": 0.01,
  "CASH_average_credit_trxn_value": 0.01,
  "CASH_average_trxn_value": 0.01,
```

"CASH_avg_monthly_num_credit_trxns_last_3m": 0,
"CASH_min_monthly_num_credit_trxns_last_3m": 0,
"CASH_min_monthly_num_credit_trxns_last_6m": 0,
"CASH_max_monthly_num_credit_trxns_last_9m": 0,
"CASH_min_monthly_num_credit_trxns_last_9m": 0,
"CASH_avg_num_monthly_trxns_last_12m": 0,
"CASH_avg_num_monthly_debit_trxns_last_12m": 0,
"CASH_avg_monthly_num_credit_trxns_last_12m": 0,
"CASH_max_monthly_num_credit_trxns_last_12m": 0,
"CASH_min_monthly_num_credit_trxns_last_12m": 0,
"CASH_ratio_num_trxns_1m": 0,
"CASH_ratio_num_trxns_9m": 0,
"INVESTMENT_CountDebitAmount_Current": 0,
"INVESTMENT_SumCreditAmount_Current": 0,
"INVESTMENT_average_credit_trxn_value": 0.01,
"INVESTMENT_max_num_monthly_debit_trxns_last_3m": 0,
"INVESTMENT_avg_monthly_debit_trxn_value_last_3m": -0.01,
"INVESTMENT_avg_monthly_num_credit_trxns_last_3m": 0,
"INVESTMENT_min_monthly_num_credit_trxns_last_3m": 0,
"INVESTMENT_avg_monthly_credit_trxn_value_last_3m": 0,
"INVESTMENT_min_monthly_credit_trxn_value_last_3m": 0,
"INVESTMENT_max_num_monthly_trxns_last_6m": 0,
"INVESTMENT_min_num_monthly_debit_trxns_last_6m": 0,
"INVESTMENT_max_monthly_num_credit_trxns_last_6m": 0,
"INVESTMENT_min_monthly_num_credit_trxns_last_6m": 0,
"INVESTMENT_avg_monthly_num_credit_trxns_last_9m": 0,
"INVESTMENT_min_monthly_num_credit_trxns_last_9m": 0,
"INVESTMENT_min_monthly_trxn_value_last_12m": -0.01,
"INVESTMENT_avg_monthly_credit_trxn_value_last_12m": 0,
"INVESTMENT_ratio_AvgBalance_9m": 0,
"Age": 0,
"HasCurrent_Account_Current": "Yes",
"HasSavings_Current": "Yes",
"HasTerm_Deposit_Current": "Yes",
"HasRevolving_Credit_Current": "No",
"HasTerm_Loan_Current": "No",
"HasMortgage_Current": "No",
"HasLeasing_Current": "No",
"DepsBalance_Current": 0,
"diff_NumProducts_1m": -5,
"diff_NumProducts_9m": -7,
"LG_EXTERNAL_ID": "Customer_123"
},
{

"CASH_AvgBalance_Current": 100,
"CASH_average_debit_trxn_value": 2.01,
"CASH_average_credit_trxn_value": 3.01,
"CASH_average_trxn_value": 4.01,
"CASH_avg_monthly_num_credit_trxns_last_3m": 1,
"CASH_min_monthly_num_credit_trxns_last_3m": 1,
"CASH_min_monthly_num_credit_trxns_last_6m": 1,
"CASH_max_monthly_num_credit_trxns_last_9m": 1,
"CASH_min_monthly_num_credit_trxns_last_9m": 1,
"CASH_avg_num_monthly_trxns_last_12m": 0,
"CASH_avg_num_monthly_debit_trxns_last_12m": 0,
"CASH_avg_monthly_num_credit_trxns_last_12m": 0,
"CASH_max_monthly_num_credit_trxns_last_12m": 0,
"CASH_min_monthly_num_credit_trxns_last_12m": 0,
"CASH_ratio_num_trxns_1m": 0,
"CASH_ratio_num_trxns_9m": 0,
"INVESTMENT_CountDebitAmount_Current": 0,
"INVESTMENT_SumCreditAmount_Current": 0,
"INVESTMENT_average_credit_trxn_value": 0.01,
"INVESTMENT_max_num_monthly_debit_trxns_last_3m": 0,
"INVESTMENT_avg_monthly_debit_trxn_value_last_3m": -0.01,
"INVESTMENT_avg_monthly_num_credit_trxns_last_3m": 0,
"INVESTMENT_min_monthly_num_credit_trxns_last_3m": 0,
"INVESTMENT_avg_monthly_credit_trxn_value_last_3m": 0,
"INVESTMENT_min_monthly_credit_trxn_value_last_3m": 0,
"INVESTMENT_max_num_monthly_trxns_last_6m": 0,
"INVESTMENT_min_num_monthly_debit_trxns_last_6m": 0,
"INVESTMENT_max_monthly_num_credit_trxns_last_6m": 0,
"INVESTMENT_min_monthly_num_credit_trxns_last_6m": 0,
"INVESTMENT_avg_monthly_num_credit_trxns_last_9m": 0,
"INVESTMENT_min_monthly_num_credit_trxns_last_9m": 0,
"INVESTMENT_min_monthly_trxn_value_last_12m": -0.01,
"INVESTMENT_avg_monthly_credit_trxn_value_last_12m": 0,
"INVESTMENT_ratio_AvgBalance_9m": 0,
"Age": 0,
"HasCurrent_Account_Current": "No",
"HasSavings_Current": "Yes",
"HasTerm_Deposit_Current": "Yes",
"HasRevolving_Credit_Current": "No",
"HasTerm_Loan_Current": "No",
"HasMortgage_Current": "Yes",
"HasLeasing_Current": "No",
"DepsBalance_Current": 0,
"diff_NumProducts_1m": 2,

"diff_NumProducts_9m": 4,
"LG_EXTERNAL_ID": "Customer_456"
}],
"modelKey": "abc-123-456-789-def",
"detailed": "false",
"dataSource": "live",
"probability": true
}

API Response Structure:

The user has the option to choose between a standard response and a detailed response. The standard response contains the model score and a URI to view the explainable output.

The standard response is shown in Figure 2 Basic API Response Structure.

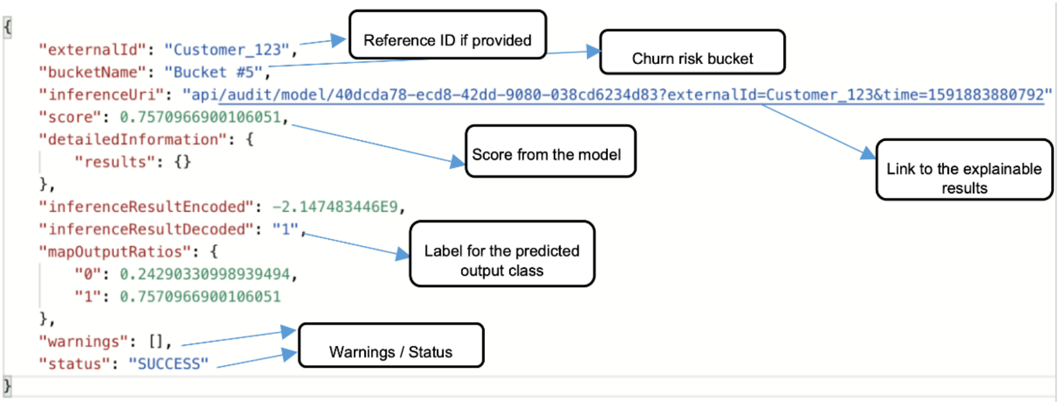


Figure 2 Basic API Response Structure

By default, the probability of attrition is not displayed; however this can be received in the response by setting the “probability” top level request field to Boolean value *true.* Note that a default bucketing must exist for the model on the XAI platform for the probability to be defined.

In Figure 2 Basic API Response Structure, the key ‘detailedInformation’ does not contain any results ({‘results’:{}}. Detailed information can be used to format the response in a custom UI or to perform further analysis on individual rules / drivers for customer inferences. Detailed response can be activated by setting the flag ‘detailed’ to ‘True’ in the API request payload. An example of a part of results contained within ‘detailedInformation’ is shown in Figure 3 . All other response information is the same as contained within the standard response.

```json
{
    "externalId": "Customer_123",
    "bucketName": "Bucket #5",
    "inferenceUri": "api/audit/model/40dcda78-ecd8-42dd-9080-038cd6234d83?externalId=Customer_123&time=1591884960949",
    "score": 0.7570966900106051,
    "detailedInformation": {
        "results": {
            "detailedResults": [
                {
                    "rank": 1,
                    "name": "0",
                    "overall": 0.24290330998939494,
                    "rules": [
                        {
                            "firingStrength": 1.0,
                            "dominance": 9.676901266189984E-4,
                            "ratioAsPercentage": 0.0663632567961808,
                            "antecedent": [
                                {
                                    "field": "Has_Current_Product_Current",
                                    "value": "1.0"
                                },
                                {
                                    "field": "CASH_min_num_monthly_debit_trxns_last_9m",
                                    "value": "0"
                                }
                            ],
                            "ruleId": 355,
                            "dominanceRating": 3.0,
                            "label": "0"
                        },
                        {
                            "firingStrength": 1.0,
                            "dominance": 9.061005935858247E-4,
                            "ratioAsPercentage": 0.062139505944327135,
                            "antecedent": [
                                {
                                    "field": "INVESTMENT_min_num_monthly_trxns_last_9m",
                                    "value": "0"
                                },
                                {
                                    "field": "Has_Current_Product_Current",
```


Figure 3 Partial Detailed Response

Recall that the results from batch inferencing are then streamed back (either as XML to Temenos Analytics or as XML/JSON to the client directly). The streamed results contain an additional field which appears immediately after each “score” field, namely a “probability” field that converts each model score between 0 and 1 to an actual probability of attrition between 0 and 1. A second additional field would also be present if the bank has also acquired the Temenos Customer Lifetime Value (LTV) XAI model, namely “ltv”. This is shown in Figure 4, which shows a single inference extracted from a streamed response (without detailedInformation for brevity).


```xml
▼<result>
   <ltv type="float">108.0654430282218867</ltv>
  ▼<inference>
     <externalId type="str">Customer_123</externalId>
     <bucketName type="str">Bucket #1</bucketName>
    ▼<inferenceUri type="str">
       api/audit/model/40dcda78-ecd8-42dd-9080-038cd6234d83?externalId=Customer_123&time=1593534127145
     </inferenceUri>
     <score type="float">0.015902591003423172</score>
     <probability type="str">0.0005517045700842138</probability>
    ▼<detailedInformation type="dict">
       <results type="dict"/>
     </detailedInformation>
     <inferenceResultEncoded type="float">-2147483445.0</inferenceResultEncoded>
     <inferenceResultDecoded type="str">0</inferenceResultDecoded>
    ▼<mapOutputRatios type="dict">
       <n0 type="float">0.9840974089965768</n0>
       <n1 type="float">0.015902591003423176</n1>
     </mapOutputRatios>
     <warnings type="list"/>
     <status type="str">SUCCESS</status>
   </inference>
</result>
```

Figure 4 Single XML Response

5. Functionality

5.1 API Behaviours

Banks can integrate the interaction with the attrition model API based easily within their pipeline. They can also choose a level of customisation based on their own requirements as the API response contains all necessary information for them to be able to consume the results within their own UI, if needed.

Variations	Expected Results:
“detailed” flag set to true in request	Response contains a detailed set of rules fired for the request
Feature value for continuous features derived from the payload falls outside the ‘seen’ values by the model (see Appendix C for seen range for relevant features)	The response contains warning/s about the values which fall outside the range but will still return a valid response with score and URI
Prediction score/probability cannot be derived from the payload	Model returns an error response.
Fields other than prediction score/probability cannot be derived from the payload	Model treats the missing values as ‘Null’ and returns a valid response

5.2 Rules and drivers

For every valid response returned by the model – the inference URI shows a detailed ‘Rules’ view of the rules applicable to the customer’s inference and a condensed ‘Driver’ view of the most important features-value combinations applicable to the inference.

The attrition model’s explainable decisions assist the end-user by presenting its reason for the output score on a driver (feature) and rule basis.

Each *IF-THEN* rule has an underlying dominance, which is derived from

- the prevalence of the rule within all instances used to train the model and,
- the accuracy of the rule

For any given instance, then all the rules that are applicable to that particular case are collated according to their ‘*firing strength’*. The firing strength of a rule depends on to what degree an instance satisfies the rule condition.

Finally, from all the rules that have ‘*fired*’, all the premise that make up the rules are combined to get a driver level importance.

An example of the two views from the same customer inference is shown in Figure 5 and Figure 6.

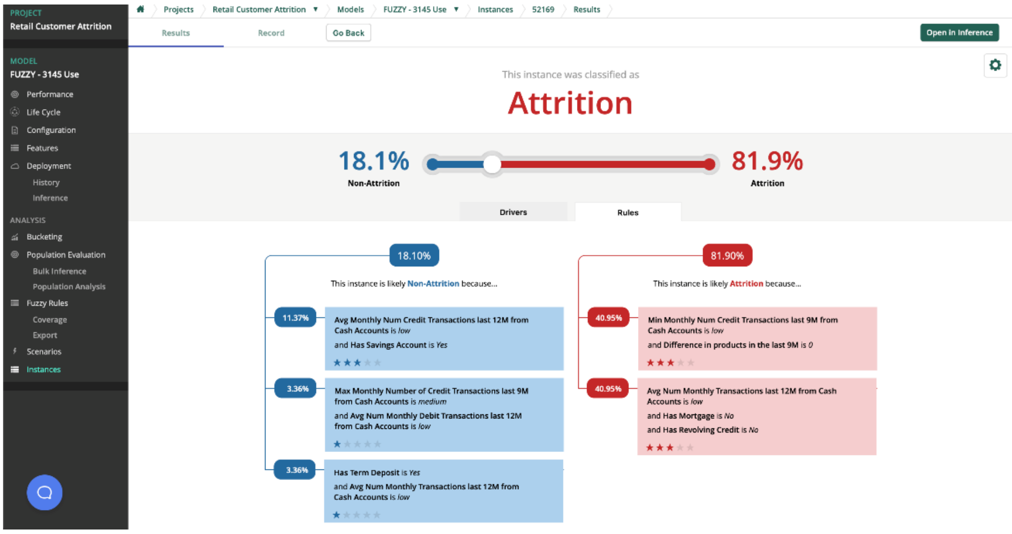


Figure 5 Rule View

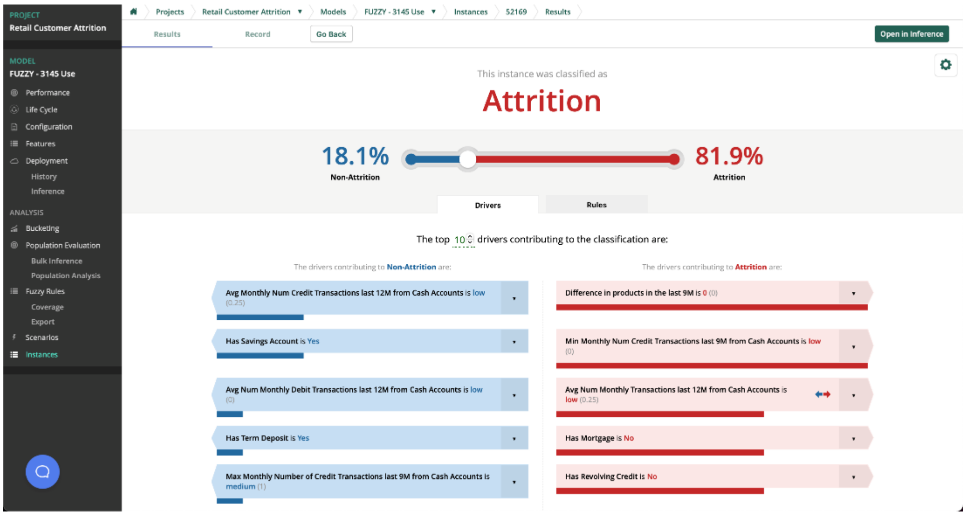


Figure 6 Driver View

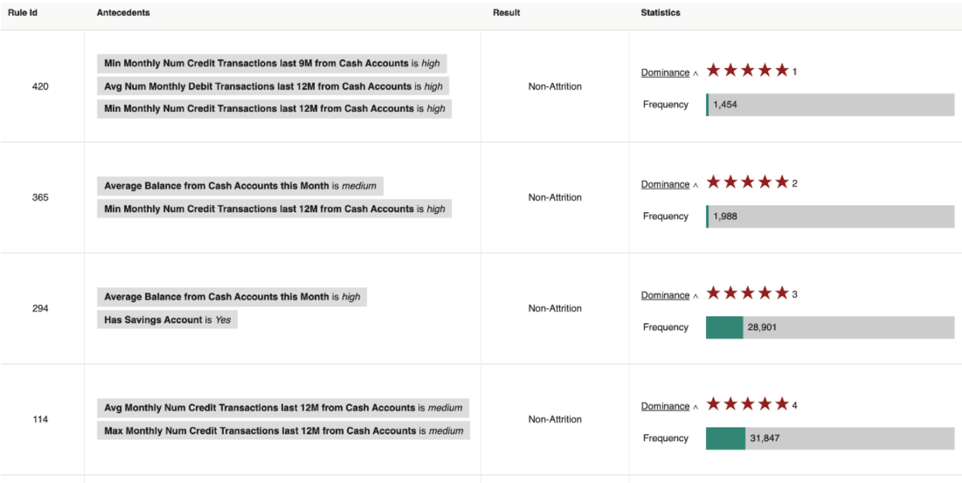
5.3 Model rule base

The model has a transparent global rule base for arriving at individual instance scores and the same can be viewed by going to the model page and then clicking 'Analysis' → 'Rules'. The rules are by default ordered by their importance to the model. Each rule in the rulebase shows:

- The 'Antecedent' part (the premise/s which make up the rule),
- The rule statistics (not meaningful for models generated using expert opinion and synthetic data) and

- The class that the rule points towards.

Transparency of model logic allows end-users to have faith in the model actions as well as comply with any regulatory requirements. The attrition model's fully transparent rule base captures complex interactions between input features while being explainable.



Rule Id	Antecedents	Result	Statistics
420	Min Monthly Num Credit Transactions last 9M from Cash Accounts is *high* Avg Num Monthly Debit Transactions last 12M from Cash Accounts is *high* Min Monthly Num Credit Transactions last 12M from Cash Accounts is *high*	Non-Attrition	Dominance ★★★★★ 1 Frequency 1,454
365	Average Balance from Cash Accounts this Month is *medium* Min Monthly Num Credit Transactions last 12M from Cash Accounts is *high*	Non-Attrition	Dominance ★★★★★ 2 Frequency 1,988
294	Average Balance from Cash Accounts this Month is *high* Has Savings Account is *Yes*	Non-Attrition	Dominance ★★★★★ 3 Frequency 28,901
114	Avg Monthly Num Credit Transactions last 12M from Cash Accounts is *medium* Max Monthly Num Credit Transactions last 12M from Cash Accounts is *medium*	Non-Attrition	Dominance ★★★★★ 4 Frequency 31,847

Figure 7 - Example of High Dominance Rules in Rule Base

5.4 Scenario Analysis

The model supports changes in form of addition/modifications/deletions to its rule base conditional on the modifications involving valid input values.

Banks can be in full control of the model by augmenting the initial rule base with their own domain expertise. This also allows them to be fully in control even if the economic or customer landscape has changed and they would like the rule base to reflect the changes before the actual customer churn data starts picking up on the changes. This allows the banks to be always in sync with the economic and customer cycles by being flexible around their attrition modelling approach.

Changes to a model's rule base can be made via the scenario functionality offered by the Temenos XAI platform. A new scenario can be created for an attrition model by adding/modifying/deleting rules from the existing rule base.

From the model page – going to 'Analysis' → 'Scenarios' → 'Create New Scenario' (Figure 8) will create a new scenario with a user specified name – which by default is the same as the underlying rule base.

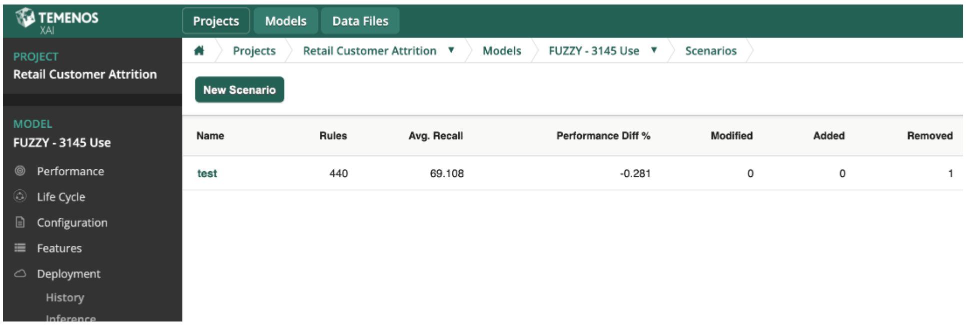


Figure 8 Create a new Scenario

Once a scenario has been created – rules can be added, deleted or modified.

- To add a rule, click ‘Add Rule’ button as shown in Figure 9 and Figure 100:

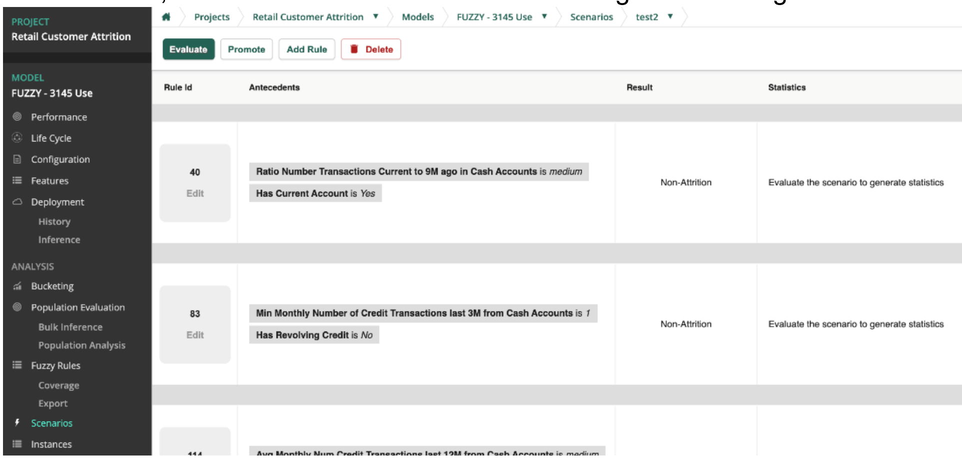


Figure 9 Add Rule Button

- In the dialogue box that appears select the feature along with the value that is applicable for the rule. If needed, select more premises for the Antecedent part of the rule. Select the right Target Class and the rule dominance. The rule dominance is between 1 and 5 with 1 being a weak rule and 5 being a dominant rule. Press Save Rule. This will add the rule to the scenario.

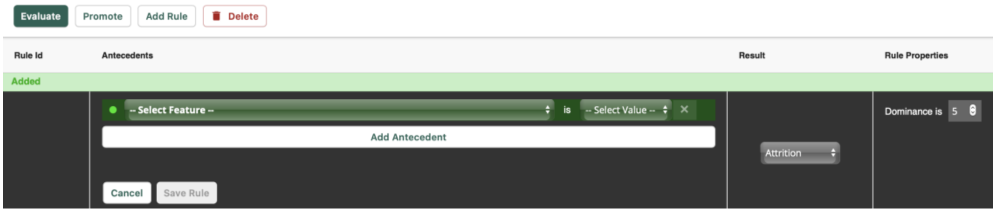


Figure 10 Adding a Rule

- To delete a Rule, select a rule by filtering on Rule Id or by manually finding the rule. Select Edit. On the resulting screen – select ‘Delete Rule’. This will delete the rule from the scenario. (Figure 111)

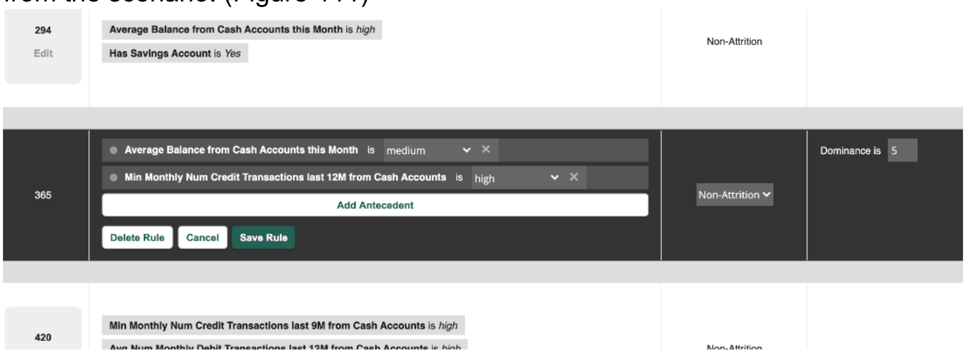


Figure 11 Deleting a Rule

- To edit a rule, select the desired rule to edit as in previous step. Now change any/all of antecedents, associated feature values, rule dominance and Target Class. Once rule has been edited as desired – press ‘Save Rule’. This will replace the original rule in the scenario with the edited rule.
- Once all the desired changes have been made to a scenario. It can be evaluated for a shift in performance. The evaluation can be performed as often as a user likes – after every rule change or after some/all changes have been made. The evaluation is

done on the main scenario screen by pressing the Evaluate button (Figure 122) with the performance change shown in a pop-up on the screen (Figure 133).

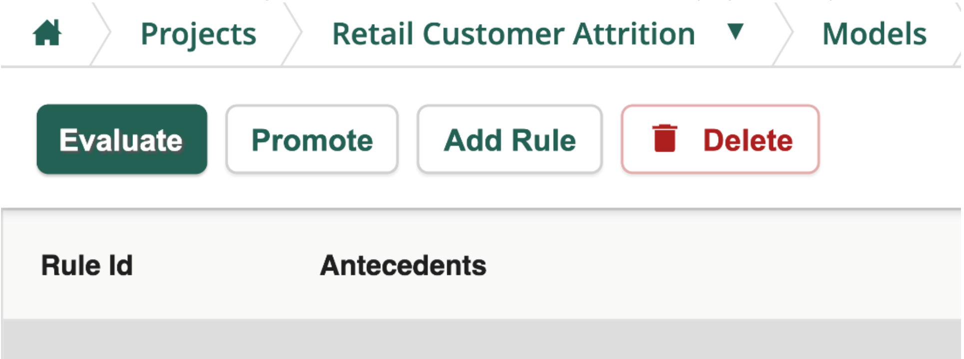


Figure 12 Evaluate Rule Button

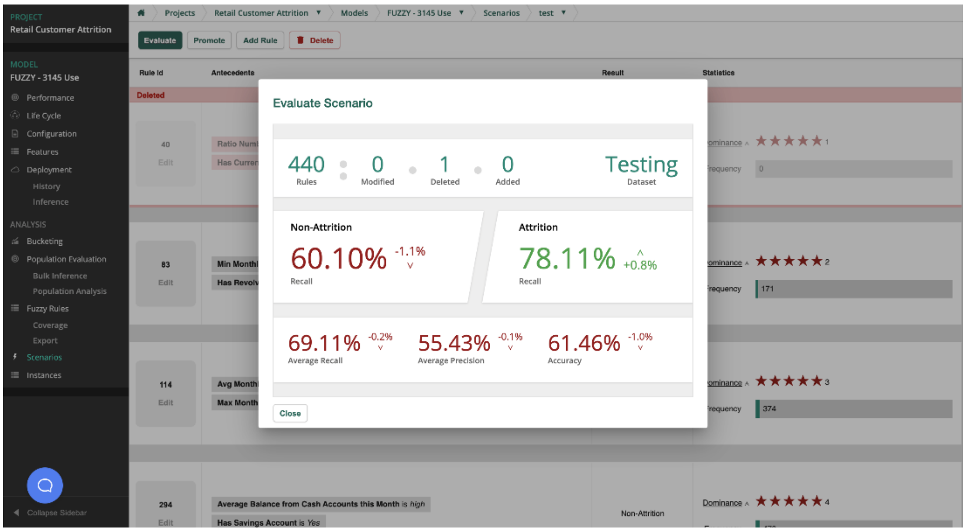


Figure 13 Evaluating the Scenario Performance

- At this stage the scenario has all the desired changes but it is not yet a model. To convert a scenario to a model, press the ‘Promote’ button on the main scenario screen (Figure 14) and it will be built as a model in the background and will appear in the models list once the build has finished.

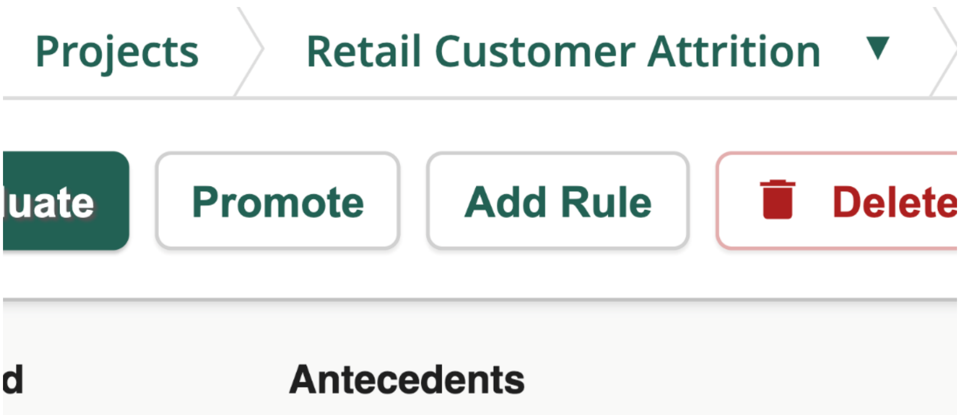


Figure 14 Promote a Scenario to a Model

Variations	Expected Results:
Rule being added already exists in the rule base	The platform shows an error message saying the Rule already exists in the Rule Base and gives the Id of the existing Rule. Duplicate / conflicting rules cannot be added to the rule base.
Rule being added can be derived from combination of other rules in the rule base	The platform gives a warning that the rule can be derived from other rules – but still allows the user to add the rule to the rule base.

5.5 Bucketing

Understanding historical attrition risk-based behaviour of customers allows the bank to consider and employ different strategies to retain customers in different churn risk buckets

The bucketing tool allows a user to segment customers with known outcomes to be segmented in risk-buckets and helps in understanding how each risk bucket performed. The instances all scored by the attrition model and are assigned scores between 0 and 1. The bucketing widget then groups the customers falling within a certain range – say 0 to 0.25 and presents statistics like number of instances falling in this range. Custom statistics can be added by the user based on the information available within the record. The platform has various goal seek tools like setting the number of buckets, equalizing the number of instances within buckets, setting bucket boundaries based on number of instances /minority instances required in each bucket etc.

Bucketing can be accessed clicking on the model and then visiting ‘Analysis’ → ‘Bucketing’ as shown in Figure 16. The user is free to choose a plotted feature for the y-axis; typically this is left at the default of “Instance Count”.

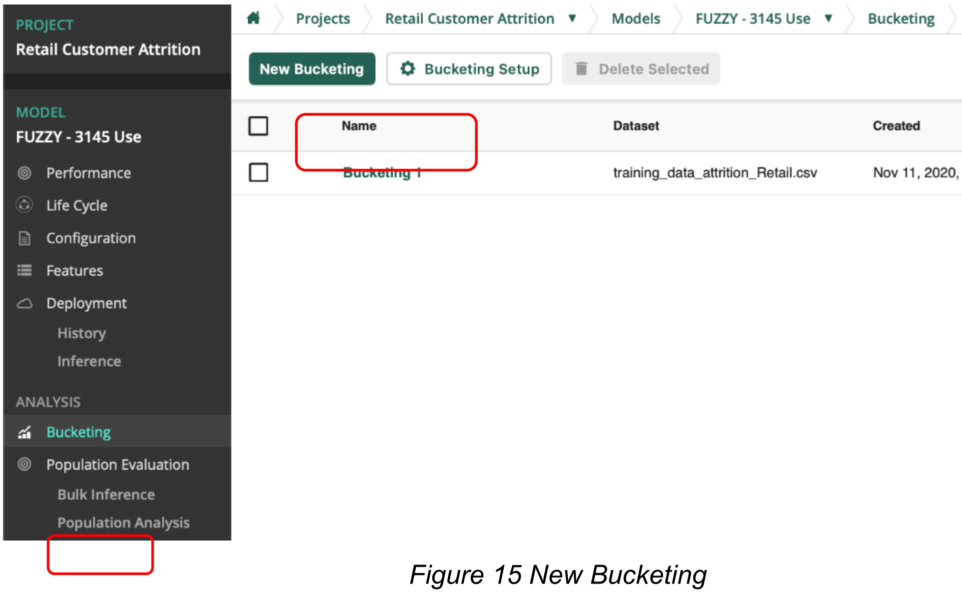


Figure 15 New Bucketing

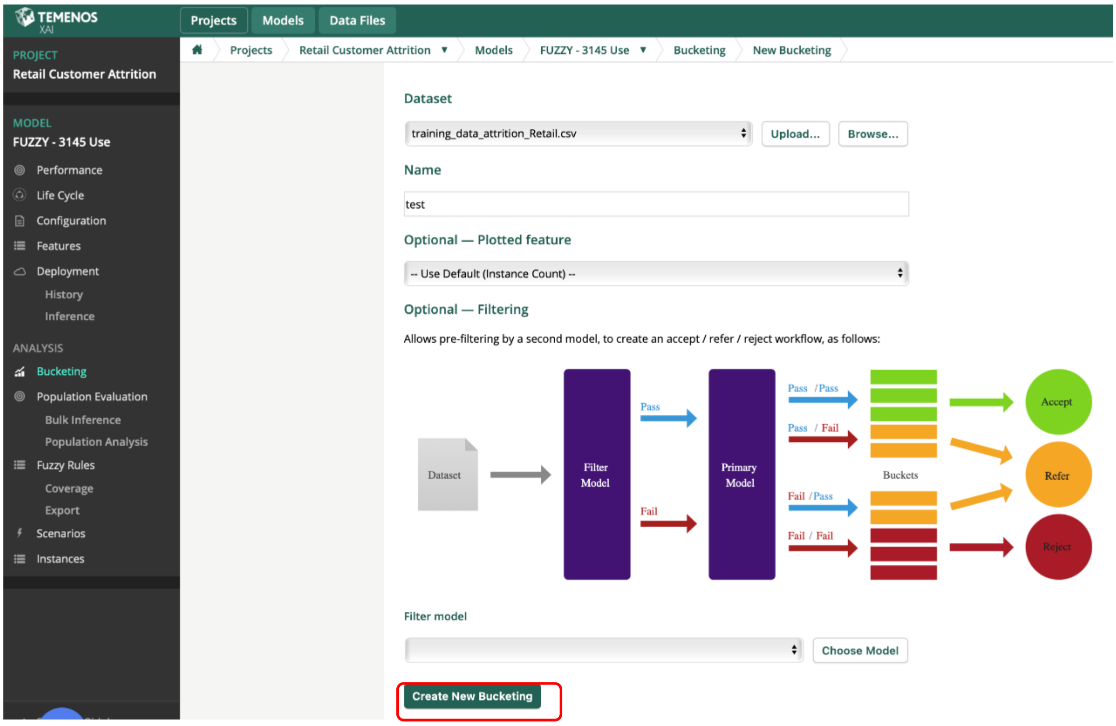


Figure 16 Create Bucketing

A screenshot of a bucketing is shown in Figure 17 Bucketing. The highlighted area shows where the options for changing bucket counts and using various goal seek scenarios are listed. Note the options to edit the default bucketing are disabled once the model is deployed.

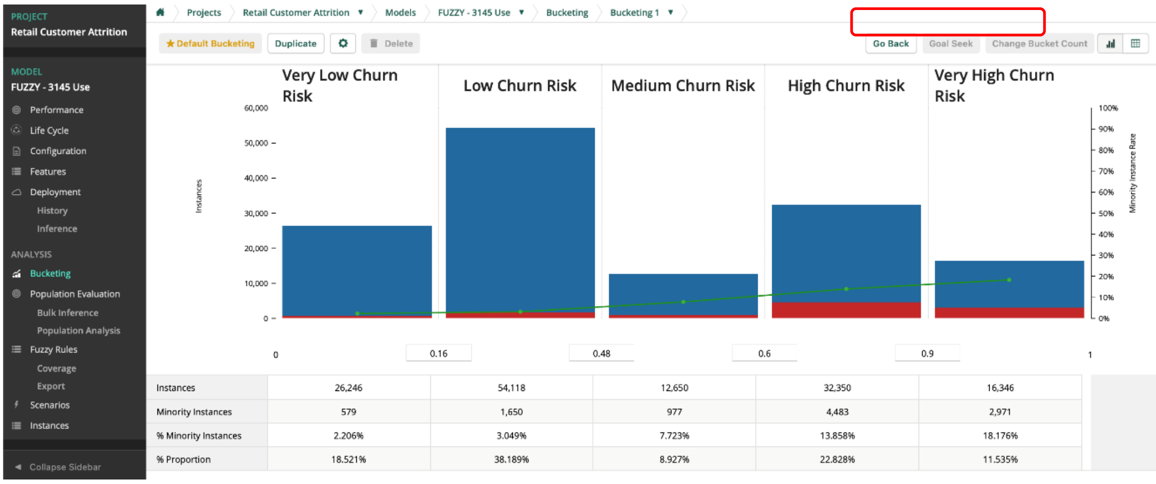


Figure 17 Bucketing

Variations	Expected Results:
The data file for bucketing does not contain the target class / outcome column	The platform shows an error message - “The uploaded file is missing the expected target column, "Outcome".
The data file is missing feature column/s which were used to train the model.	The platform shows an error message – “An unknown error occurred while creating the bucketing.”

5.6 "What if" demo inferences

User can examine the changes in scores arising from a change to any/all the input value/s.

The bank might wish to provide understand actions which will enable the attrition risk to be reduced at the level of individual customers.

The features or attributes which need improving can be taken from the explanation provided for the score. Once the user knows which attributes for the customer are causing the high attrition risk, the instance can be opened in the ‘Inference Viewer’ and the user can pass different values for the attributes that need improvement to see how this will affect the score.

As an example, consider the explainable output (driver view) in **Error! Reference source not found.** for an instance which scores 0.750. From the driver view, it can be seen that the lack of a mortgage is negatively impacting the score.

Note also that if the user clicks on the name of a continuous feature, the fuzzy set ranges for are displayed (as shown in Figure 19 Fuzzy Set Ranges for Feature).

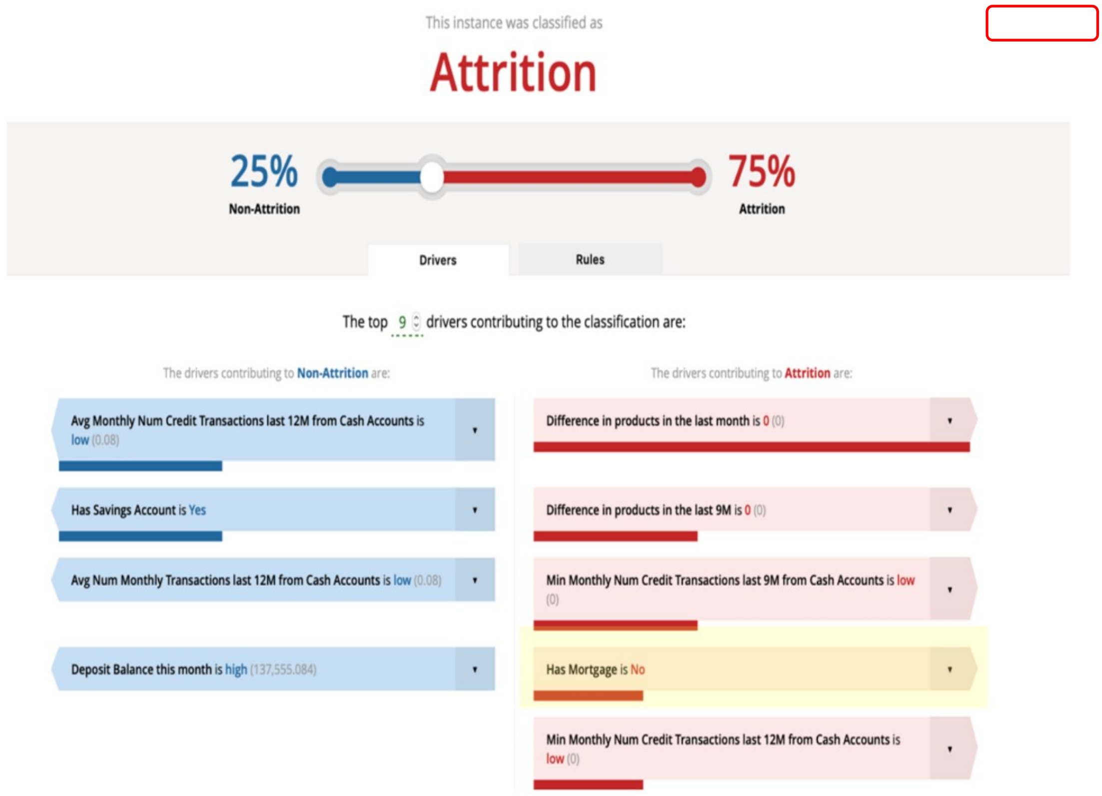


Figure 18 High Churn Risk Customer

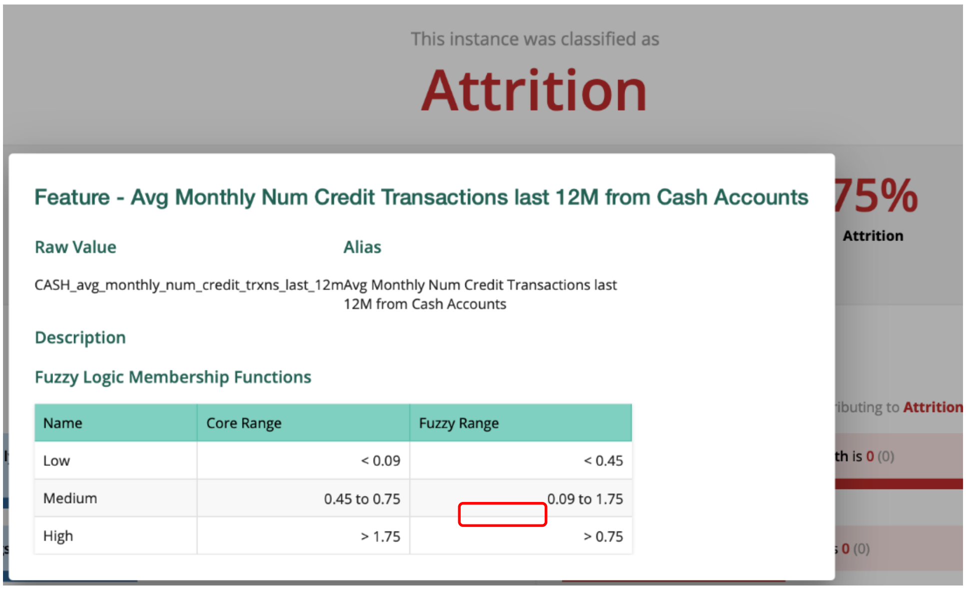


Figure 19 Fuzzy Set Ranges for Feature

The user clicks the ‘Open Inference’ button (highlighted in **Error! Reference source not found.**) and this takes them to the page shown in Figure 200. On this page, the user can change the value of the selected feature (has internet banking service) to the label ‘1.0’ and click the predict button to see the updated score. The score improves to 0.500 as shown in Figure 22 Updated Model Score. If this is an acceptable score, the user may choose to promote mortgage incentives to this customer in the knowledge that this corresponds to increased engagement with the bank i.e. a lower attrition risk.

Figure 20 Inference Viewer

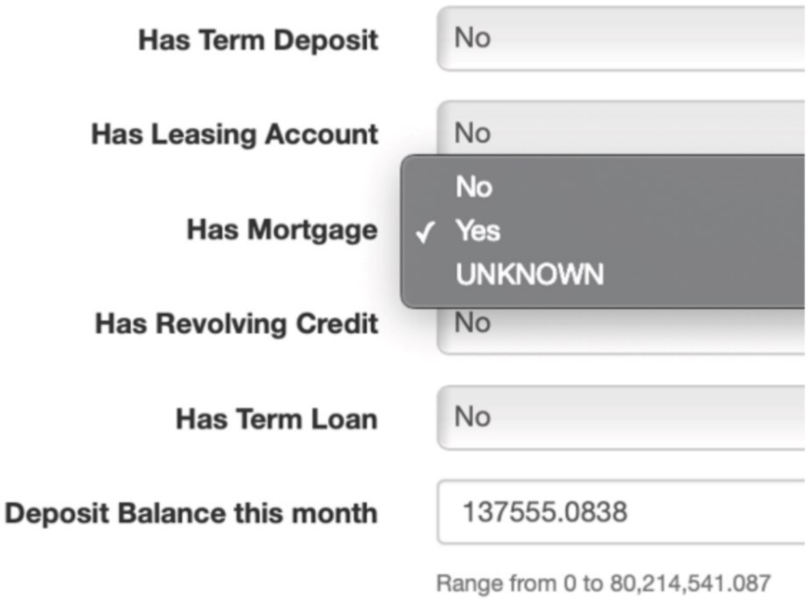


Figure 21 Changing Feature Value

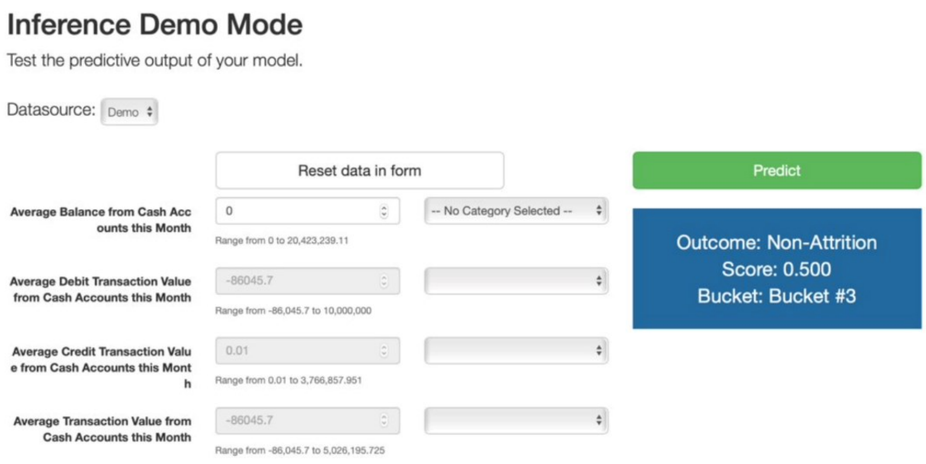


Figure 22 Updated Model Score

5.7 Model Monitoring

The user is provided the tools required to decide on whether the model needs retraining or not. This depends on:

1. Whether the distribution of scores on live instances follows a similar pattern to the training data set.
2. Whether the live instances have similar feature value distributions to the ones used in the training data set

Deciding on whether to continue with the current model or train a new one on more recent data is usually a business-critical decision that all clients running predictive models need to make at regular intervals. The need to retrain models can arise from a shift in economic environment and/or shift in the business policies leading to a different customer segments being passed through the model.

The platform allows a user to conduct 'Population Stability Analysis' and 'Characteristic Stability Analysis' to address points 1 and 2 respectively.

The usage is shown in the screenshots below:

To start – load the file with the data on instances that need to be tested for stability analysis. The file should contain all feature columns that were present in the original training data file in the same order. This is done from Analysis → Population → Bulk Inference as shown in Figure 23. View the bulk inference once it has run and press Perform Analysis as per Figure 24.

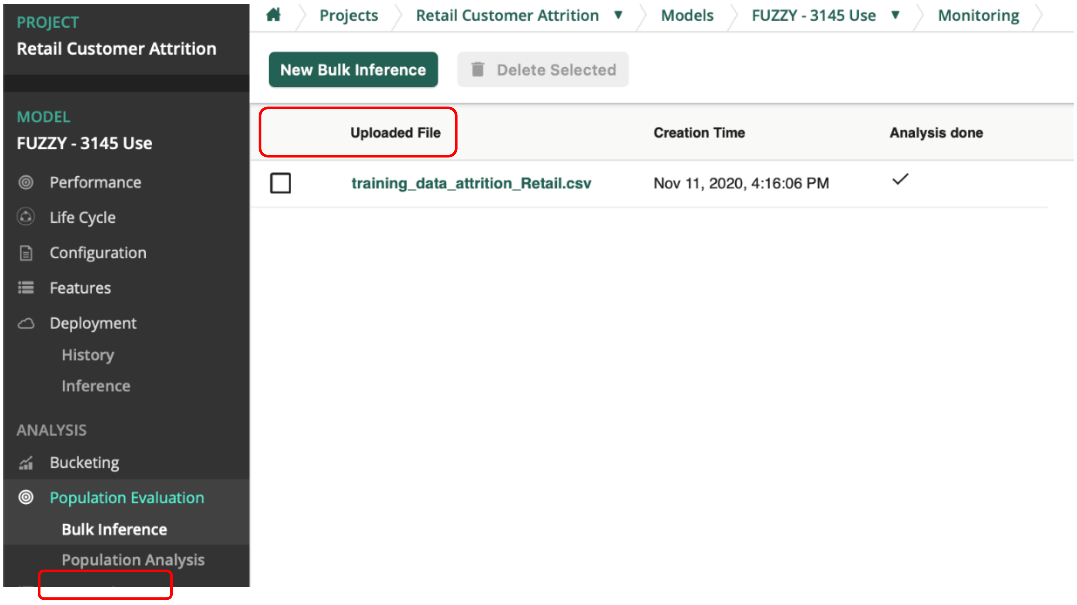


Figure 23 Create A Bulk Inference

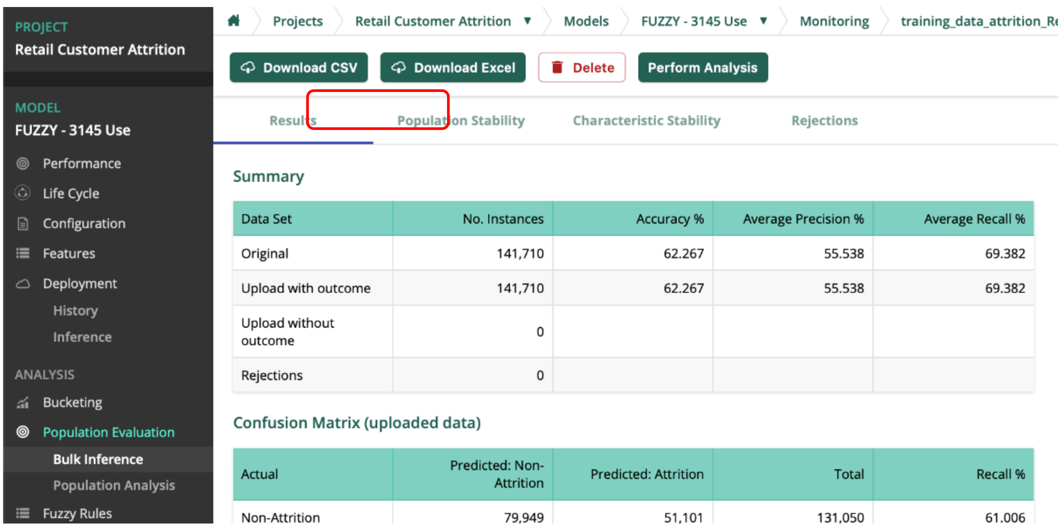


Figure 24 Perform Analysis

Population stability is a useful measure to see how the new instances are scoring compared to the training population. This can be seen visually as proportion of instances falling under each bucket of the default bucketing. The uploaded data refers to the new instances and the original data refers to the data used to build the model. An example of Population Stability is shown in Figure 25 Population Stability.

Temenos XAI platform can also do analysis at the level of each feature. This can be seen under the tab 'Characteristic Stability'. The information under this tab compares the distribution of each feature in the new instances versus the original instances. This analysis in useful in identifying values which might be entered incorrectly or where the values have shifted due to a change in the economic conditions or the type of customers. Features, where the distribution has shifted significantly are highlighted in red, as shown in Figure 26 Characteristic Stability

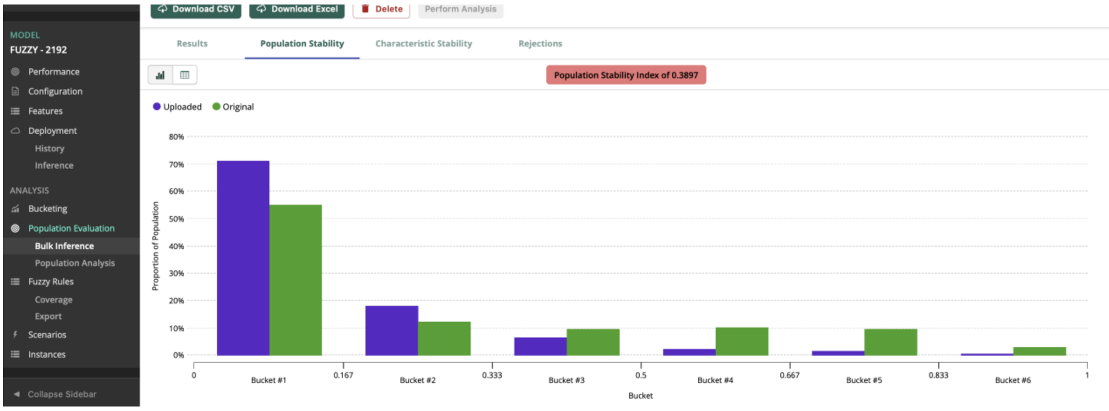
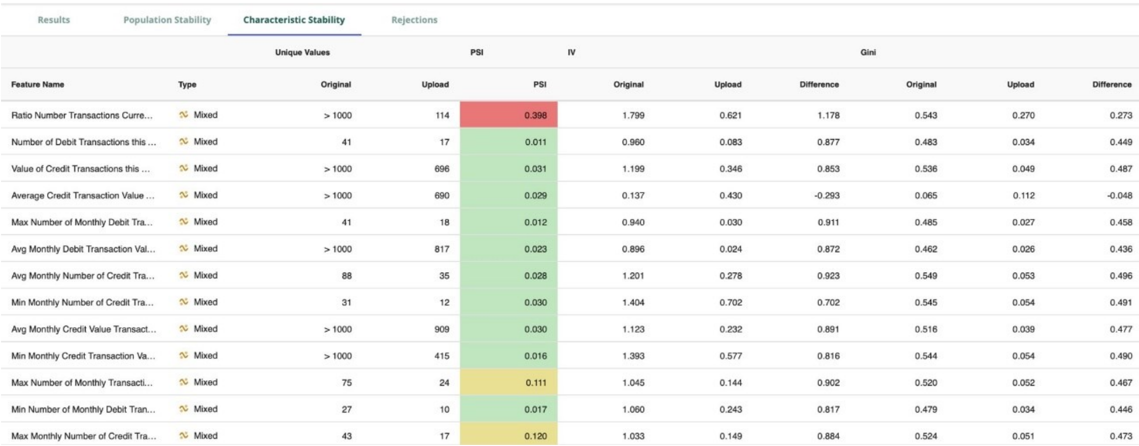


Figure 25 Population Stability



		Unique Values		PSI	IV			Gini		
Feature Name	**Type**	**Original**	**Upload**	**PSI**	**Original**	**Upload**	**Difference**	**Original**	**Upload**	**Difference**
Ratio Number Transactions Curre...	Mixed	> 1000	114	0.398	1.799	0.621	1.178	0.543	0.270	0.273
Number of Debit Transactions this ...	Mixed	41	17	0.011	0.960	0.083	0.877	0.483	0.034	0.449
Value of Credit Transactions this ...	Mixed	> 1000	696	0.031	1.199	0.346	0.853	0.536	0.049	0.487
Average Credit Transaction Value ...	Mixed	> 1000	690	0.029	0.137	0.430	-0.293	0.065	0.112	-0.048
Max Number of Monthly Debit Tra...	Mixed	41	18	0.012	0.940	0.030	0.911	0.485	0.027	0.458
Avg Monthly Debit Transaction Val...	Mixed	> 1000	817	0.023	0.896	0.024	0.872	0.462	0.026	0.436
Avg Monthly Number of Credit Tra...	Mixed	88	35	0.028	1.201	0.278	0.923	0.549	0.053	0.496
Min Monthly Number of Credit Tra...	Mixed	31	12	0.030	1.404	0.702	0.702	0.545	0.054	0.491
Avg Monthly Credit Value Transact...	Mixed	> 1000	909	0.030	1.123	0.232	0.891	0.516	0.039	0.477
Min Monthly Credit Transaction Va...	Mixed	> 1000	415	0.016	1.393	0.577	0.816	0.544	0.054	0.490
Max Number of Monthly Transacti...	Mixed	75	24	0.111	1.045	0.144	0.902	0.520	0.052	0.467
Min Number of Monthly Debit Tran...	Mixed	27	10	0.017	1.060	0.243	0.817	0.479	0.034	0.446
Max Monthly Number of Credit Tra...	Mixed	43	17	0.120	1.033	0.149	0.884	0.524	0.051	0.473

Figure 26 Characteristic Stability

5.8 Feature set augmentation

The user can add expert knowledge on sparsely available attributes/features to the model.

In times of sudden changes to the economic landscape – new variables might become relevant for which there is no historical data available. Since the attrition model is a rule based approach with rules in human understandable form – it is possible to add rules to the original rule base containing patterns from the newly identified feature. The rules to be added are not a complex as the ones generated from the data as there is typically not much information available to understand complex interactions between features. However – it is a useful and unique starting point to make use of human expertise along with data-based insights. The process involves some complexity and needs to be carried out by Temenos AI data science team to make sure that the resulting model is as robust as the original model.

5.9 Model Deployment

The user can deploy models with ease and speed – and monitor the inferences being passed through the deployed model/s.

Fast and easy deployment is essential for banks looking to either retraining the models with new data or upgrading current models with expert knowledge.

Temenos AI platform offers a 1-click cloud deployment for models as shown in Figure 27.

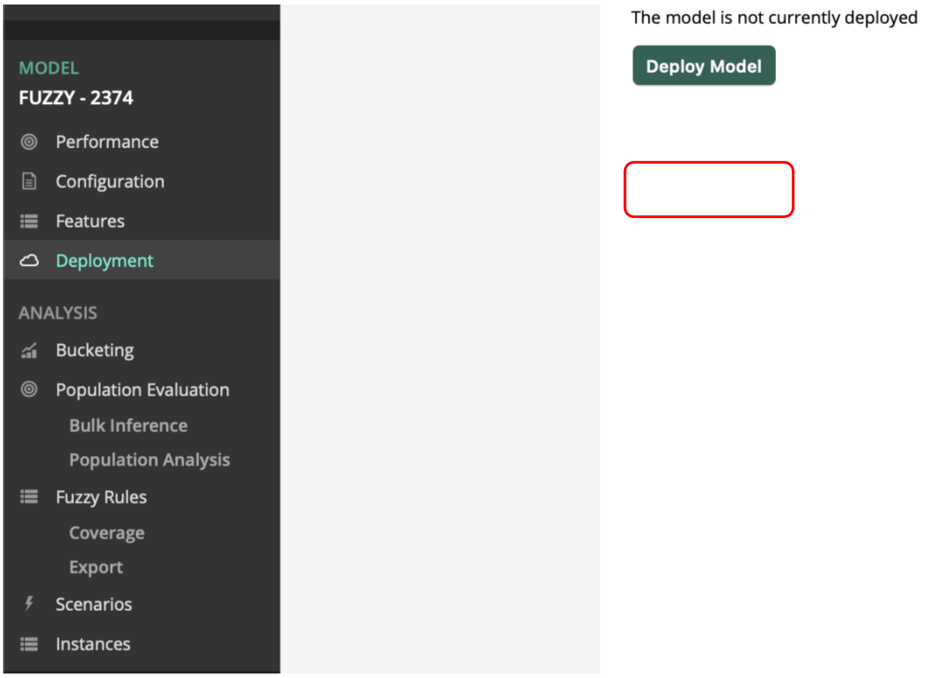


Figure 27 1-Click Model Deployment

5.10 GUI Inferences

The user can interact with the model using a GUI based inference page, without the need to send an API call to the model. The inference results will have an option to be stored in the database.

Some users may not have the need or the technical know-how for integrating API calls within their infrastructure. For such users - the Temenos AI platform provides an easy way to interact with the model.

The UI based inference page can be opened from 'Deployment' → 'Inference'. The resulting page opens in a new browser tab and is shown in Figure 28. The features that need to be input on this page need to be pre-calculated by the client (using the same logic as in the preprocessing, i.e. ETL, layer) and usually, the Temenos AI team can provide a spreadsheet/script with all necessary calculations for the same. In Figure 28, if the Datasource (highlighted) is set to 'Live', then all results will be stored in the database and can be accessed from the 'History' tab on the 'Deployment' page.

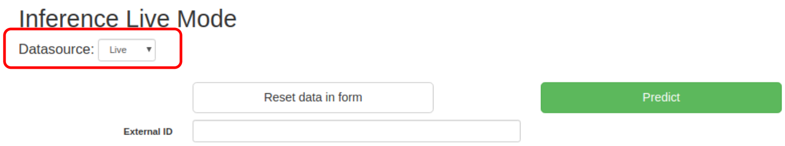


Figure 28 UI based Inference Page

5.11 Custom Fuzzy Sets

Prior to any models being built on a project, the user can define custom fuzzy sets for continuous features. Note at present the user must be in an administrator role to access this functionality.

By default, the platform uses a distribution based method to define the fuzzy sets such that, essentially, ‘low’, ‘medium’ and ‘high’ linguistic labels are represented equally often in the uploaded data. The following threshold values are necessary and sufficient to define the trapezoidal interval type-2 fuzzy sets used by the platform, with the usual three linguistic labels:

- ‘low’ core end/’ medium’ upper start
- ‘low’ lower end/ ‘medium’ lower start
- ‘low’ upper end/ ‘medium’ core start
- ‘medium’ core end/ ‘high’ upper start
- ‘medium’ lower end/ ‘high’ lower start
- ‘medium’ upper end/ ‘high’ core start

By default these six thresholds are defined such that they divide the data into heptiles with close to an equal number of instances in each subset.

However the user may wish to define their own fuzzy sets, so that the definitions of low, medium and high are consistent with the conventional understanding of these labels in their own business domain. To do so they are free to redefine these six key threshold values.

The user can therefore reach ‘Features’ → ‘All Features’ and click a continuous feature, and then click ‘Change Range for MFs’ to change the membership functions for the fuzzy sets, as shown in Figure 29 and Figure 30.

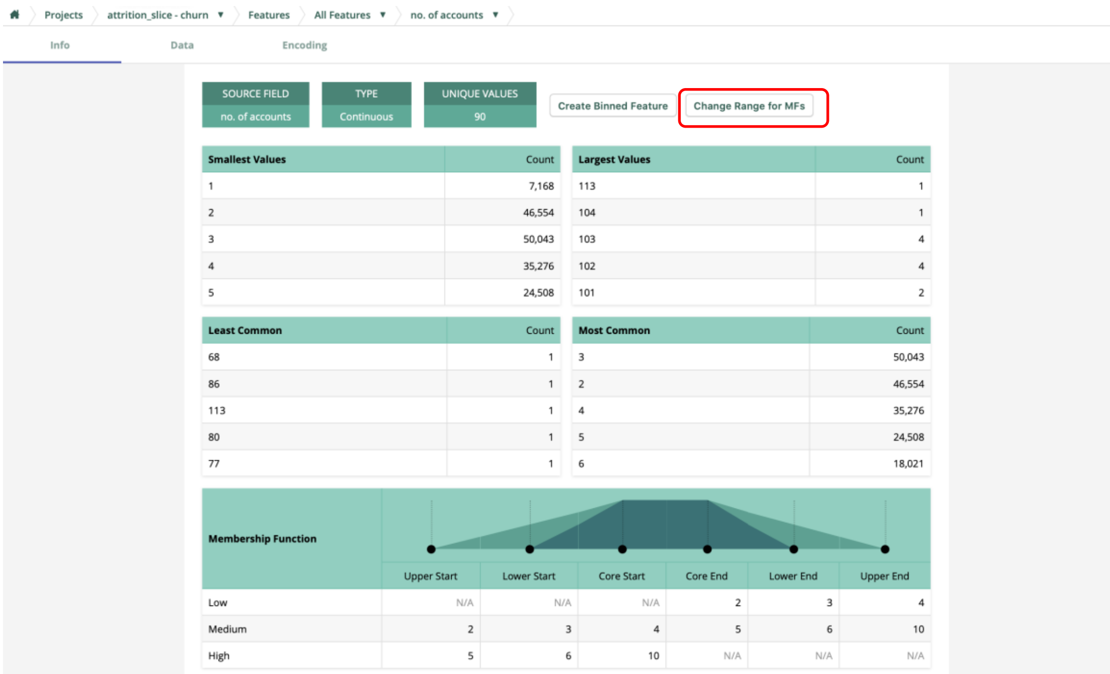


Figure 29

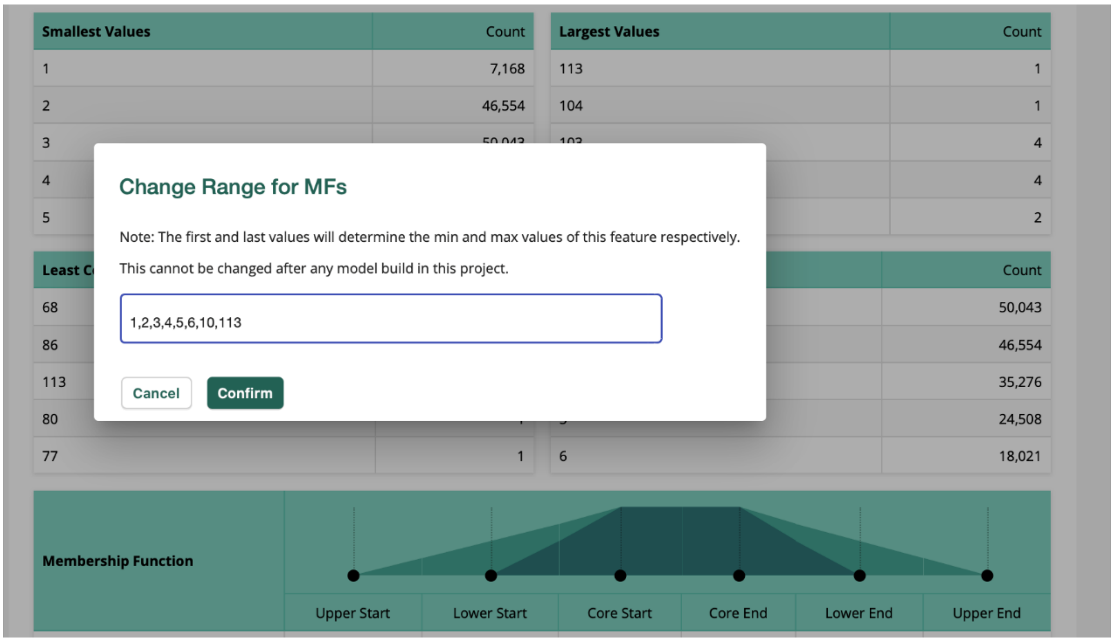


Figure 30

Note there are eight values shown in Figure 30 as the lowest and highest represent the minimum and maximum values for that feature observed in the uploaded data.

5.12 Customer Segmentation

The XAI Platform provides click-thru functionality such that clicking on a bucket (see Section 5.5) displays a breakdown of the contributions of fuzzy rules to that bucket. Actions taken to reduce the churn risk of each customer can be informed by the general behaviour of the bucket they fall in to, as well as the rules that fire for the individual customer

As per Figure 31 below for the medium risk bucket, we see customers in this bucket are likely to change their behaviour if incentivised to take on new products.

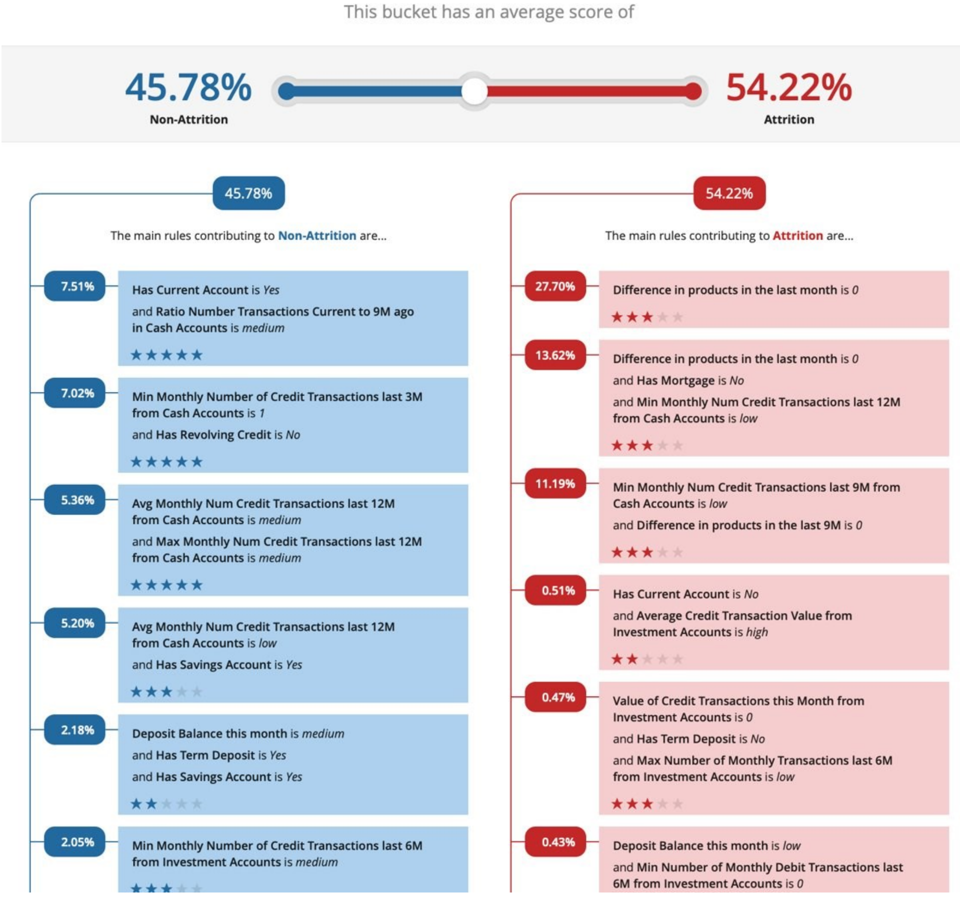


Figure 31

Longer term products such as mortgages are particularly effective in increasing retention, as are current accounts which significantly increase customer engagement with the bank. For both the medium and high risk buckets (the latter shown in Figure 32), a strategy of marketing or incentivising the uptake of new products may be considered.

Figure 32

5.13 Production Inferencing

If the bank is using the pre-built solution that integrates the Temenos XAI platform with Temenos Data Warehouse and Temenos Analytics Platform. At run time the request containing the ‘raw information’ from the data warehouse and other optional information hits the XAI endpoint. The XAI endpoint performs further processing to derive the feature set that is used to obtain inferences from the model. Some post-processing is applied to the model JSON response which is then streamed back to Analytics Platform as XML.

This SQL-processed data is programmatically uploaded as a CSV to the XAI live preprocessing service, which performs the same python feature engineering steps as were carried out on the original training data. These same preprocessing steps are wrapped into a robust web framework, which also provides a UI for visual demo inferences. The service can return either an XML or JSON (shown left) response structure; if the results are returned to Temenos Analytics then this will be as XML.

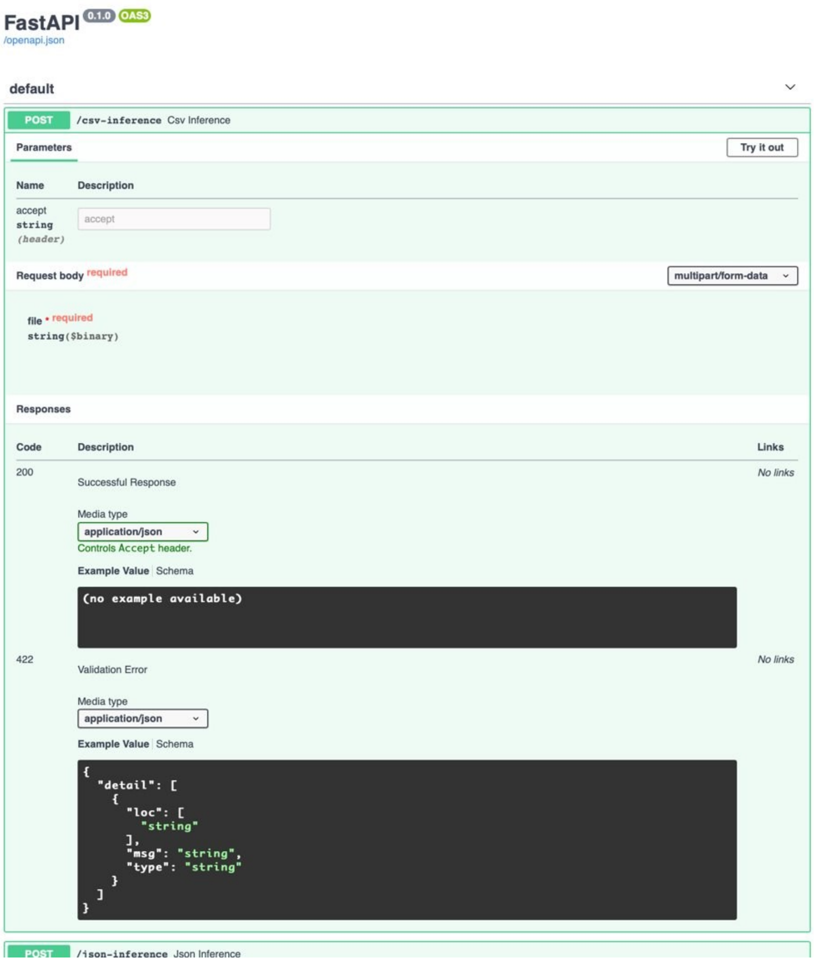

FastAPI 0.1.0 OAS3
/openapi.json
default
POST /csv-inference Csv Inference
Parameters
Try it out
Name
Description
accept
string
(header)
accept
Request body required
multipart/form-data
file * required
string($binary)
Responses
Code
Description
Links
200
Successful Response
No links
Media type
application/json
Controls Accept header.
Example Value Schema
(no example available)
422
Validation Error
No links
Media type
application/json
Example Value Schema
{
"detail": [
{
"loc": [
"string"
],
"msg": "string",
"type": "string"
}
]
}
POST /json-inference Json Inference

Figure 33

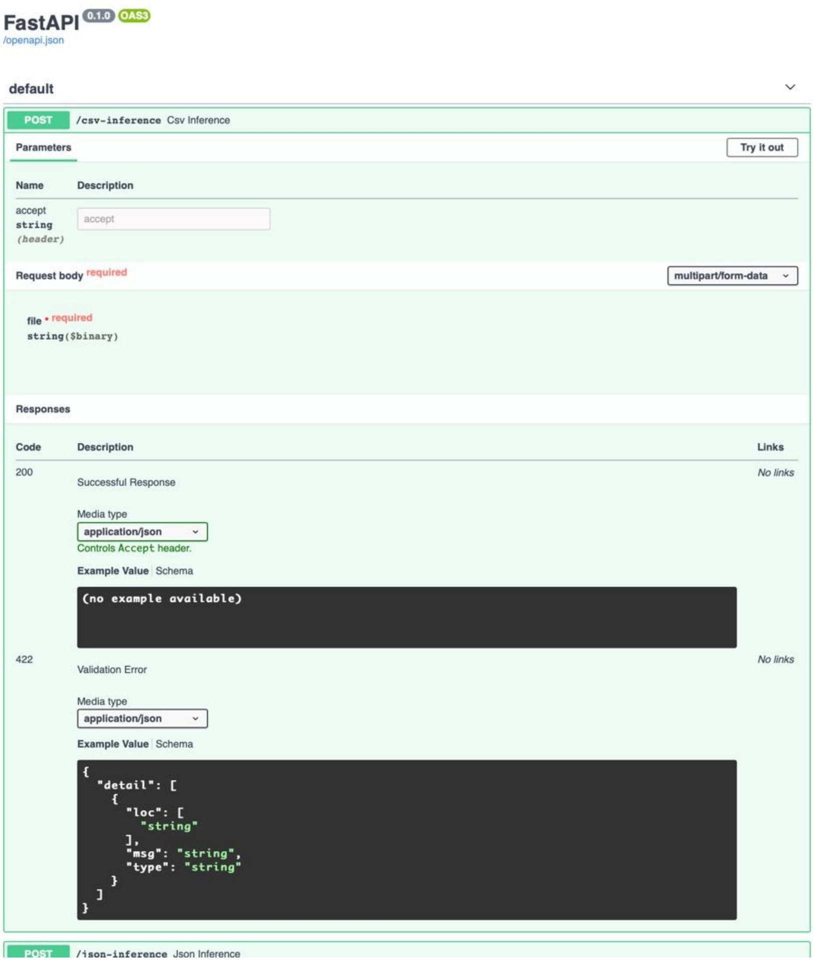


Figure 34

The python service acts as a proxy in front of the core XAI Platform, handling data preprocessing, batch inferencing and also post-processing of the XAI platform's API response.

The containerised application is highly portable, providing flexibility in the cloud deployment in order to meet.

Figure 35

Model results are stored back into the TEMENOS Analytics Data Warehouse. A Data Relationship and Dataset can now be created, merging the results with customer data, allowing for the creation of analytical dashboards

Figure 36

6. Configuration / Customization

For each client – the ETL layer needs to be coded if the data source being used is not already supported.

7. Assumptions

This document is based on assumption that clients will use the cloud version of the attrition model and Temenos AI platform. For on premise installations, there would be a separate step of configuring /installing the platform and model in client infrastructure.

8. Exclusions

Any requirements arising from on-premise installations are excluded from this document.