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ARTIFICIAL INTELLIGENCE (AI) BASED METHODS AND SYSTEMS FOR MAXIMIZING CREDIT CARD REVENUE

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TITLE: "ARTIFICIAL INTELLIGENCE (AI) BASED METHODS AND SYSTEMS FOR MAXIMIZING CREDIT CARD REVENUE"

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TECHNICAL FIELD

[0001] This disclosure relates generally to the field of Artificial Intelligence (AI) and finance. More particularly, the present disclosure is related to AI based methods and systems for maximizing credit card revenue.

BACKGROUND

[0002] Generally, majority of bank revenue for credit card portfolio comes from interest payments revenue and this solution directly influences interest income earnings of the bank. Such interest payment revenue may be a combined product of revolving balances, interest margin and repayment rate. Whereas the commission revenue may be a combined product of total amount spent and the commission. Therefore, total bank revenue earned based on the credit card portfolio may be indicated as shown in the below equations.

Bank Revenue = Fees + Interest Revenue + Commission Revenue
= Fees + (Revolving Balances x Interest Margin x Repayment Rate)
+ (Total Spend x Commission)

[0003] Currently, though the bank revenue from the credit card portfolio comes from the interest payments, the existing techniques are not sufficient and effective in capturing the need of the user in order to stimulate spending, building the revolving balance, identifying target segments, predicting user requirements and the like. Due to this ineffectiveness, many account holders are not seeking credit cards, and the account holders who have credit cards are not using it to its potential which could enhance the interest payment revenue for the banks. Moreover, existing techniques are not AI based models due to which the existing techniques are unable to effectively analyze, learn, predict and target based on the existing data in various data sources. Therefore, there is a need to build a comprehensive and robust AI based solution that addresses the issues ranging from stimulating spending to building the revolving balance to check balance leakages. Such solution should be capable of taking into consideration individual business problems and bring all of them together for identifying target segments with a suitable action.

SUMMARY

[0004] According to some non-limiting embodiments, the present disclosure leverages Artificial Intelligence (AI) to develop and identify interaction between complex layers of customer behaviour to maximize client revenue and enhance customer experience. The objective of the present disclosure is to develop and put together powerful AI models that are configured to:

- Induce spending by personalizing offers and communications for credit card users, that are tailored towards customer need. This in turn maximizes the customer spend wallet share and maximizes interchange revenue;
- Identify potential revolvers in the portfolio to give the potential revolvers a right line of credit and treatment to enrich their revolving experience based on a propensity model;
- Grow balances by converting low revenue generating transactors into high yield revolvers;
- Build portfolio balance through installment loan sell based on segmented targeting and pricing;
- Proactively, identify potential attritors, manage attrition of valued customers to stop the portfolio leakage;
- Perform predictive model development using machine learning models to implement the aforementioned objectives. In some non-limiting embodiments, a combination of Hive, Python, Statistical Analysis System (SAS) and specialized machine learning libraries may be used for developing the model. Therefore, such models are easily deployable at the client end.

[0005] In some non-limiting embodiments, the present disclosure decomposes a business problem into individual components, builds a solution and stitches all of them together to generate an optimal solution for each individual component. In other words, each of the AI models developed to implement the aforementioned objectives may be clustered together using Machine Learning (ML) clustering techniques, to build a strong, powerful, robust and a comprehensive model that can maximize credit card portfolio revenue. In some embodiments, the software associated with the developed AI models are packaged in such a way that, it can be deployed in both conventional and latest data platform framework at ease.

[0006] In some non-limiting embodiments, the present disclosure creates a comprehensive machine learning solution by developing AI powered business decisioning process for power growth with issuers credit card portfolio. In some embodiments, the method of the present disclosure includes obtaining data from one or more data sources such as Visa Net, issuer data, bureau data and so on. In some embodiments, the Visa Net may provide transaction data such as issuer country, market segment, merchant name, source and destination amounts, plastic type, channel and so on. In some embodiments, the issuer may provide data such as demographics (income, age, nationality, etc.), product vintage, balances, credit card related indicators. The combined data received from Visa Net and Issuer may result in derived data such as age bins by market segments, and nationality and merchant name count. In some embodiments, the method includes acquiring potential revolvers using data received from various sources, to analyze and understand resolving behavior for a period, for achieving sharper customer experience (Module 1). Further, in some embodiments, the method includes recommending hybrid market using client data and market segment data, to provide right category offer to right customer for multiplying engagement level of the customer (Module 2) (e.g., to grow spending's of customers) based on batch scoring/prediction service, and real-time scoring/prediction service. Furthermore, in some embodiments, the method includes predicting transactors turned into revolvers, using issuer data, for identifying potential revolvers and curate an engagement path for customers (Module 3) (for example, integration with bank infrastructure for monthly targeting via spend offers i.e. grow balances). Thereafter, in some embodiments, the method includes predicting installment using issuer data, for growing inorganic balances (in other words, installments) (Module 4) (for example, integration with bank infrastructure for monthly targeting via Below-The-Line (BTL) channels like tele-calling, electronic Direct Mail (eDM) and Short Message Service (SMS). Further, in some embodiments, the method includes predicting Attrition using issuer data, for controlling spend leakage and customer churn, to retain customers (Module 5) (e.g., Integration with Bank Infrastructure for monthly Retention practice) based on model score and policy parameter to create action segments to target retention efforts. Finally, in some embodiments, the method includes combining the output of modules 1-5 for creating clusters of customers exhibiting similar behavior (Module 6) (e.g., Cluster based Targeting: Targeted actions for each segment based on current engagement levels, card utilization, propensity to revolve/Easy Payment Plan (EPP) and risk of attrition) and recommending personalized offers and communication to the consumer.

[0007] The present research work provides an advantage in influencing the significant component of the banking revenue driver by decomposing the problem into individual components, building the solution and combining all together for finding optimal actions. The solution acquires revenue generating revolvers and maximizes customer spend wallet share, which in turn maximizes interchange revenue to the bank. This solution converts the low revenue generating transactors to high yield revolvers and also proactively manages attrition of valued customers.

[0008] These and other features and characteristics of the present invention, as well as the methods of operation and functions of the related elements of structures and the combination of parts and economies of manufacture, will become more apparent upon consideration of the following description and the appended claims with reference to the accompanying drawings, all of which form a part of this specification, wherein like reference numerals designate corresponding parts in the various figures. It is to be expressly understood, however, that the drawings are for the purpose of illustration and description only and are not intended as a definition of the limits of the invention. As used in the specification and the claims, the singular form of “a,” “an,” and “the” include plural referents unless the context clearly dictates otherwise.

BRIEF DESCRIPTION OF THE DRAWINGS AND APPENDICES

[0009] Additional advantages and details of non-limiting embodiments are explained in greater detail below with reference to the exemplary embodiments that are illustrated in the accompanying schematic figures, in which:

[0010] FIG. 1A discloses a schematic diagram of a system for acquisition of potential revolvers according to some principles of the present disclosure;

[0011] FIG.1B shows exemplary key features and model performance of a revolver model that enables acquisition of potential revolvers and increasing their spends through targeted recommendations, according to some principles of the present disclosure;

[0012] FIG.2A discloses a schematic diagram of a system for hybrid market recommendation according to some principles of the present disclosure;

[0013] FIG.2B shows an exemplary hybrid merchant recommender in accordance with some principles of the present disclosure;

[0014] FIG. 3A discloses a schematic diagram of a system for identifying low revenue generating transactors who can be turned into high yield revolvers according to some principles of the present disclosure;

[0015] FIG.3B shows exemplary key features and model performance of a revolve prediction model that enables identifying transactors who are likely to be converted into revolvers and increasing their spends through targeted recommendations, according to some principles of the present disclosure;

[0016] FIG.4A discloses a schematic diagram of a system for identifying customers for instalment loan sell according to some principles of the present disclosure;

[0017] FIG.4B shows exemplary key features and model performance of an instalment prediction model that enables identifying customers who are likely to buy products through instalment plans and increasing their spends through targeted recommendations, according to some principles of the present disclosure;

[0018] FIG.5A discloses a schematic diagram of a system for identifying customer attrition according to some principles of the present disclosure;

[0019] FIG.5B shows exemplary key features and model performance of a balance attrition model that enables identifying customers who are likely to attrite in a few months, and performing targeted actions to retain such customers, according to some principles of the present disclosure;

[0020] FIG. 6 discloses a schematic diagram of a system showing a solution that combines all solutions disclosed in the present disclosure together for finding optimal actions according to some principles of the present disclosure.

[0021] FIG.7 discloses a schematic diagram of an architecture showing an Ending Net Receivables (ENR) scoring and optimization engine according to some principles of the present disclosure;

[0022] FIG.8 shows an exemplary PyModel deployment for using Jupyter® as service used for preparing data for performing feature extraction and model building, according to some principles of the present disclosure;

[0023] FIG.9 shows an exemplary PyModel deployment for using Machine Learning (ML) service for generating batch predictions and real-time predictions, according to some principles of the present disclosure;

[0024] FIG.10 shows an exemplary PyModel deployment for using Visa REST Application Programming Interface (API) for communicating with the Artificial Intelligence Platform (AIP), according to some principles of the present disclosure;

[0025] FIG.11 shows an exemplary PyModel for building and training models using Multi Layer Perceptron (MLP), according to some principles of the present disclosure;

[0026] FIG. 12 shows a flowchart that illustrates a method for Artificial Intelligence (AI) enabled credit card revenue maximizer, according to a non-limiting embodiment; and

[0027] FIG. 13 is a block diagram of an exemplary computer system for implementing embodiments consistent with the present disclosure.

DESCRIPTION OF THE DISCLOSURE

[0028] In the present document, the word "exemplary" is used herein to mean "serving as an example, instance, or illustration." Any embodiment or implementation of the present subject matter described herein as "exemplary" is not necessarily to be construed as preferred or advantageous over other embodiments.

[0029] While the disclosure is susceptible to various modifications and alternative forms, specific embodiment thereof has been shown by way of example in the drawings and will be described in detail below. It should be understood, however that it is not intended to limit the disclosure to the particular forms disclosed, but on the contrary, the disclosure is to cover all modifications, equivalents, and alternative falling within the spirit and the scope of the disclosure.

[0030] The terms “comprises”, “comprising”, or any other variations thereof, are intended to cover a non-exclusive inclusion, such that a setup, device or method that comprises a list of components or steps does not include only those components or steps but may include other components or steps not expressly listed or inherent to such setup or device or method. In other words, one or more elements in a device or system or apparatus proceeded by “comprises… a” does not, without more constraints, preclude the existence of other elements or additional elements in the device or system or apparatus.

[0031] The terms "an embodiment", "embodiment", "embodiments", "the embodiment", "the embodiments", "one or more embodiments", "some embodiments", and "one embodiment" mean "one or more (but not all) embodiments of the invention(s)" unless expressly specified otherwise.

[0032] The terms "including", "comprising", “having” and variations thereof mean "including but not limited to", unless expressly specified otherwise.

[0033] For purposes of the description hereinafter, the terms “end,” “upper,” “lower,” “right,” “left,” “vertical,” “horizontal,” “top,” “bottom,” “lateral,” “longitudinal,” and derivatives thereof shall relate to the invention as it is oriented in the drawing figures. However, it is to be understood that the invention may assume various alternative variations and step sequences, except where expressly specified to the contrary. It is also to be understood that the specific devices and processes illustrated in the attached drawings, and described in the following specification, are simply exemplary embodiments or aspects of the invention. Hence, specific dimensions and other physical characteristics related to the embodiments or aspects disclosed herein are not to be considered as limiting.

[0034] As used herein, the terms “communication” and “communicate” may refer to the reception, receipt, transmission, transfer, provision, and/or the like of information (e.g., data, signals, messages, instructions, commands, and/or the like). For one unit (e.g., a device, a system, a component of a device or system, combinations thereof, and/or the like) to be in communication with another unit means that the one unit is able to directly or indirectly receive information from and/or transmit information to the other unit. This may refer to a direct or indirect connection (e.g., a direct communication connection, an indirect communication connection, and/or the like) that is wired and/or wireless in nature. Additionally, two units may be in communication with each other even though the information transmitted may be modified, processed, relayed, and/or routed between the first and second unit. For example, a first unit may be in communication with a second unit even though the first unit passively receives information and does not actively transmit information to the second unit. As another example, a first unit may be in communication with a second unit if at least one intermediary unit (e.g., a third unit located between the first unit and the second unit) processes information received from the first unit and communicates the processed information to the second unit. In some non-limiting embodiments, a message may refer to a network packet (e.g., a data packet and/or the like) that includes data. It will be appreciated that numerous other arrangements are possible.

[0035] As used herein, the term “merchant” may refer to an individual or entity that provides goods and/or services, or access to goods and/or services, to customers based on a transaction, such as a payment transaction. The term “merchant” or “merchant system” may also refer to one or more computer systems operated by or on behalf of a merchant, such as a server computer executing one or more software applications. A “point-of-sale (POS) system,” as used herein, may refer to one or more computers and/or peripheral devices used by a merchant to engage in payment transactions with customers, including one or more card readers, near-field communication (NFC) receivers, RFID receivers, and/or other contactless transceivers or receivers, contact-based receivers, payment terminals, computers, servers, input devices, and/or other like devices that can be used to initiate a payment transaction.

[0036] As used herein, the term “portable financial device” may refer to a payment card (e.g., a credit or debit card), a gift card, a smartcard, smart media, a payroll card, a healthcare card, a wrist band, a machine-readable medium containing account information, a keychain device or fob, an RFID transponder, a retailer discount or loyalty card, a mobile device executing an electronic wallet application, a personal digital assistant, a security card, an access card, a wireless terminal, and/or a transponder, as examples. The portable financial device may include a volatile or a non-volatile memory to store information, such as an account identifier or a name of the account holder.

[0037] As used herein, the term “computing device” may refer to one or more electronic devices that are configured to directly or indirectly communicate with or over one or more networks. A computing device may be a mobile or portable computing device, a desktop computer, a server, and/or the like. Furthermore, the term “computer” may refer to any computing device that includes the necessary components to receive, process, and output data, and normally includes a display, a processor, a memory, an input device, and a network interface. A “computing system” may include one or more computing devices or computers. An “application” or “Application Program Interface” (API) refers to computer code or other data sorted on a computer-readable medium that may be executed by a processor to facilitate the interaction between software components, such as a client-side front-end and/or server-side back-end for receiving data from the client. An “interface” refers to a generated display, such as one or more graphical user interfaces (GUIs) with which a user may interact, either directly or indirectly (e.g., through a keyboard, mouse, touchscreen, etc.). Further, multiple computers, e.g., servers, or other computerized devices, such as an autonomous vehicle including a vehicle computing system, directly or indirectly communicating in the network environment may constitute a “system” or a “computing system”.

[0038] It will be apparent that systems and/or methods, described herein, can be implemented in different forms of hardware, software, or a combination of hardware and software. The actual specialized control hardware or software code used to implement these systems and/or methods is not limiting of the implementations. Thus, the operation and behavior of the systems and/or methods are described herein without reference to specific software code, it being understood that software and hardware can be designed to implement the systems and/or methods based on the description herein.

[0039] Some non-limiting embodiments or aspects are described herein in connection with thresholds. As used herein, satisfying a threshold may refer to a value being greater than the threshold, more than the threshold, higher than the threshold, greater than or equal to the threshold, less than the threshold, fewer than the threshold, lower than the threshold, less than or equal to the threshold, equal to the threshold, etc.

[0040] FIG. 1A discloses a schematic diagram of a system for acquisition of potential revolvers according to some principles of the present disclosure.

[0041] In FIG. 1A, a schematic diagram of a system 100 shows a data acquisition server 102, a data preparing unit 104, a revolver model 106, and a model output unit 108. The data acquisition server 102 may receive client data from one or more data sources (not shown in the FIG.1A) associated with the data acquisition server 102. For instance, the data acquisition server 102 may be a server associated with Visa that may already store client data collected by the Visa Net (also referred as Visa Net data). As an example, the Visa Net data may include, but not limited to, Issuer country, market segment, merchant name, source and destination amounts, plastic type, channel and the like. As an example, the one or more data sources associated with the data acquisition server 102 may include, but not limited to, an Issuer and any other external source that possesses and provides data required by the data acquisition server 102. As an example, the Issuer may be a bank that has issued a credit card for a user (also referred as customer). As an example, the client data provided by the Issuer may include, but not limited to, demographics such as income, age, nationality and the like, credit card related indicators, balances, product vintage and the like. As an example, the client data provided by the Issuer may also include bureau data that helps in establishing credit worthiness of the user. In some embodiments, the client data may be provided by each of the one or more data sources in a pre-defined format. In some embodiments, the combined data derived from the Visa Net data and the client data may include, but not limited to, age bins by market segments, nationality, merchant name counts and the like. In some embodiments, the client data, the Visa Net data and the combined data may be processed using software such as Apache® Hadoop® as shown in FIG.1A, that in turn comprises Hadoop Distributed File System (HDFS) and a processing part namely MapReduce Programming model. In some embodiments, the client data, the Visa Net data and the combined data may be processed using any other software apart from Apache® Hadoop®, that can perform similar functionality. The processed data may be stored in a certain predefined format, or in other words organized in a certain predefined format using software such as Apache® Parquet™.

[0042] Thereafter, the processed data is subjected to an interactive web tool such as Jupyter® configured in the data preparing unit 104 as shown in FIG.1A, which may be a computational notebook allowing combination of software codes, computational outputs, explanatory text and multimedia resources in a single document. In some embodiments, any other software apart from Jupyter®, having similar functionality may be used in the context of the present disclosure.

Therefore, data prepared using the software such as Jupyter®, may be used to generate the revolver model 106 that undergoes an acquisition training for acquisition of potential revolvers. As an example, the revolver model 106 may be generated and trained using data mining and modeling services provided by external service provider such as Salford Systems. However, this should not be considered as a limitation of the present disclosure, as any other service provider apart from Salford Systems may be used to generate and train the revolver model 106 for acquisition of potential revolvers. In some embodiments, based on the output of the revolver model 106, the method of the present disclosure may predict potential revolvers, and understand resolving behaviour at the time of acquisition for optimal underwriting and sharper customer experience. As shown in the FIG.1A, the model output unit 108 may display the Permanent Account Number (PAN) number of a potential revolver and a propensity value indicating the tendency of the particular customer to be a potential revolver may be indicated based on the output of the revolver model. the context of credit cards, revolvers may be individual customers or a business who open a line of credit through a credit card and use the credit over time offered by the Issuer. In some embodiments, determining the potential revolvers, helps in targeting such potential revolvers with one or more recommendations in the form of personalized offers and communications. Such targeting enhances purchases and transactions of the potential revolvers, thereby enhancing the interest revenue coming from the credit cards. FIG.1B shows exemplary key features and model performance of a revolver model that enables acquisition of potential revolvers and increasing their spends through targeted recommendations, according to some principles of the present disclosure.

[0043] FIG.2A discloses a schematic diagram of a system for hybrid market recommendation according to some principles of the present disclosure.

[0044] In FIG.2A, a schematic diagram of a system 200 shows a data acquisition server 102 receiving client data from one or more data sources (not shown in the FIG.2A) associated with the data acquisition server 102. For instance, the data acquisition server 102 may be a server associated with Visa that may already store client data collected by the Visa Net (also referred as Visa Net data). As an example, the Visa Net data may include, but not limited to, Issuer country, market segment, merchant name, source and destination amounts, plastic type, channel and the like. As an example, the one or more data sources associated with the data acquisition server 102 may include, but not limited to, an Issuer and any other external source that possesses and provides data required by the data acquisition server 102. As an example, the Issuer may be a bank that has issued a credit card for a user (also referred as customer). As an example, the client data provided by the Issuer may include, but not limited to, demographics such as income, age, nationality and the like, credit card related indicators, balances, product vintage and the like. As an example, the client data provided by the Issuer may also include bureau data that helps in establishing credit worthiness of the user. In some embodiments, the client data may be provided by each of the one or more data sources in a pre-defined format. In some embodiments, the combined data derived from the Visa Net data and the client data may include, but not limited to, age bins by market segments, nationality, merchant name counts and the like. In some embodiments, the client data, the Visa Net data and the combined data may be subjected to a Multi Layer Perceptron (MLP) layers to build a market segment recommender. In some embodiments, the MLP may utilize model artifacts and Machine Learning (ML)/Deep Learning (DL) models as shown under the bracket of serialized objects in the FIG.2A. Further, the MLP may be associated with an interactive web tool such as Jupyter® as shown in FIG.2A, which may be a computational notebook allowing combination of software codes, computational outputs, explanatory text and multimedia resources in a single document. In some embodiments, any other software apart from Jupyter®, having similar functionality may be used in the context of the present disclosure. Therefore, data prepared using the software such as Jupyter®, may be used to predict future iterations of a customer using python projects as shown under the bracket of “data preparation pipeline and prediction call” in the FIG.2A.

[0045] The hybrid market segment recommender thus built may be deployed as an Artificial Intelligence Platform (AIP) for performing batch scoring/prediction service and real-time scoring/prediction service. In some embodiments, batch scoring/prediction service may include generating predictions for a set of observations at once offline and thereafter taking an action on the set of observations. In some embodiments, real-time scoring/prediction service may be providing predictions to a client in real-time/online based on a request from the client. As shown in the FIG.2A, the client side such as Issuer banks, advertisers etc., may send a request to the AIP to understand right category to be target for a right customer. The AIP capable of providing hybrid market recommendations (also referred as hybrid merchant recommender) performs batch scoring/prediction and/or real-time scoring/prediction as per requirement and provides a response to the client side. As an example, as shown in the FIG.2A, the request from the client side may include, for example, Permanent Account Number (PAN) number partially masked, gender, age bucket, nationality group, customer subsegment and salary bucket. As an example, response provided by the AIP to client side may include, but not limited to, PAN number partially masked, and prediction of categories such as airlines, automotive, electronics, insurance and the like, as shown in the FIG.2A, to be targeted for the customers falling under this bucket to enhance their engagement level and improve credit card interest revenue for the banks. In some embodiments, the predicted categories may be considered as the right categories or potential categories that may increase transactions and engagement level of particular customers. FIG.2B shows an exemplary hybrid merchant recommender in accordance with some principles of the present disclosure. In some embodiments, using exemplary key features such as Gender, Nationality, Transaction Type, Age, Salary, Transactions count and transaction amount, a LightFM hybrid algorithm can be used as shown in the FIG.2B. The LightFM hybrid recommender algorithm is used in combination with the current observed penetration of market segments to determine a next segment where the customer has the highest probability of making a spend, on the basis of the strength of association within the market segments.

[0046] FIG. 3A discloses a schematic diagram of a system for identifying low revenue generating transactors who can be turned into high yield revolvers according to some principles of the present disclosure.

[0047] In FIG. 3A, a schematic diagram of a system 300 shows a data acquisition server 102, a data preparing unit 104, a feature extraction unit 110, and a revolve prediction model 112. The data acquisition server 102 may receive client data from one or more data sources (not shown in the FIG.3A) associated with the data acquisition server 102. For instance, the data acquisition server 102 may be a server associated with Visa that may already store client data collected by the Visa Net (also referred as Visa Net data). As an example, the Visa Net data may include, but not limited to, Issuer country, market segment, merchant name, source and destination amounts, plastic type, channel and the like. As an example, the one or more data sources associated with the data acquisition server 102 may include, but not limited to, an Issuer and any other external source that possesses and provides data required by the data acquisition server 102. As an example, the Issuer may be a bank that has issued a credit card for a user (also referred as customer). As an example, the client data provided by the Issuer may include, but not limited to, demographics such as income, age, nationality and the like, product holding and account details, Ending Net Receivable **(**ENR) balances, Repayment history, card Point of Sale (PoS) activity, merchant category spends and the like. As an example, the client data provided by the Issuer may also include bureau data that helps in establishing credit worthiness of the user. In some embodiments, the client data may be provided by each of the one or more data sources in a pre-defined format. Upon collecting the client data from the issuer, the data preparing unit 104 may prepare data for feature extraction. In some embodiments, key dimensions of data preparation used by the data preparing unit 104 may include, but not limited to, identifying historical cohorts of primary accounts of customers with all information, and creating an indicator of revolve based on 'long term' transactors who have converted to revolvers in the past. In some embodiments, "long term" transactors may be customers who have not been revolvers at least for a period of 6 months.

[0048] In some embodiments, upon preparing the data based on the key dimensions as mentioned above, the feature extraction unit 110 may perform feature extraction using the client data received from the Issuer and the Visa Net data. As an example, the features extracted from the client data received from the Issuer and the Visa Net data may include, but not limited to, Demographics such as Income, Age, Nationality, MoB, segment and the like, product holding such as Account holding across Current Account Saving Account (CASA), loans and the like, Spend and Transaction Pattern such as recency, frequency, monetary value, consistency, diversity of spends and transactions, and the like, and Balance and Payment History that identifies customer as a transactor or revolver. Thereafter, the extracted features are used for building revolve prediction model 112 using gradient boosting, that identifies transactor who can be converted to potential revolvers. As an example, the revolve prediction model 112 may be generated and trained using data mining and modeling services provided by external service provider such as Salford Systems as shown in the FIG.3A. However, this should not be considered as a limitation of the present disclosure, as any other service provider apart from Salford Systems may be used to generate and train the revolve prediction model 112 for identifying transactor who can be converted into potential revolvers. In some embodiments, the output of the revolve prediction model 112 may include, but not limited to, model score and spend targets that help in creating customized spend campaigns for the identified transactors who can be converted to potential revolvers, in order to curate an engagement path for them. In some embodiments, such a revolve prediction model 112 may be integrated with bank infrastructures in order to target the identified customers on a monthly or a weekly basis via spend offers, which in turn improve expenditure of the user and may convert the user into a revolver, thereby increasing credit card interest revenue for the banks. FIG.3B shows exemplary key features and model performance of a revolve prediction model that enables identifying transactors who are likely to be converted into revolvers and increasing their spends through targeted recommendations, according to some principles of the present disclosure.

[0049] FIG.4A discloses a schematic diagram of a system for identifying customers for installment loan sell according to some principles of the present disclosure.

[0050] In FIG.4A, a schematic diagram of a system 400 shows a data acquisition server 102, a data preparing unit 104, a feature extraction unit 110, and a instalment prediction model 114. The data acquisition server 102 may receive client data from one or more data sources (not shown in the FIG.4A) associated with the data acquisition server 102. For instance, the data acquisition server 102 may be a server associated with Visa that may already store client data collected by the Visa Net (also referred as Visa Net data). As an example, the Visa Net data may include, but not limited to, Issuer country, market segment, merchant name, source and destination amounts, plastic type, channel and the like. As an example, the one or more data sources associated with the data acquisition server 102 may include, but not limited to, an Issuer and any other external source that possesses and provides data required by the data acquisition server 102. As an example, the Issuer may be a bank that has issued a credit card for a user (also referred as customer). As an example, the client data provided by the Issuer may include, but not limited to, demographics such as income, age, nationality and the like, product holding and account details, Ending Net Receivable (ENR) balances, Repayment history, card Point of Sale (PoS) activity, merchant category spends and the like. As an example, the client data provided by the Issuer may also include bureau data that helps in establishing credit worthiness of the user. In some embodiments, the client data may be provided by each of the one or more data sources in a pre-defined format. Upon collecting the client data from the issuer, the data preparing unit 104 may prepare data for feature extraction. In some embodiments, key dimensions of data preparation used by the data preparation unit 104 may include, but not limited to, identifying historical cohorts of primary accounts of customers with all information, and creating an indicator of revenue-based installment take-up based on historic behaviour of customers in the past.

[0051] In some embodiments, upon preparing the data based on the key dimensions as mentioned above, the feature extraction unit 110 may perform feature extraction using the client data received from the Issuer and the Visa Net data. As an example, the features extracted from the client data received from the Issuer and the Visa Net data may include, but not limited to, Demographics such as Income, Age, Nationality, MoB, segment and the like, product holding such as Account holding across Current Account Saving Account (CASA), loans and the like, Spend and Transaction Pattern such as recency, frequency, monetary value, consistency, diversity of spends and transactions, and the like, Balance and Payment History that identifies customer as a transactor or revolver, and Instalment History that indicates past purchases of instalment products by the customers. Thereafter, the extracted features are used for building an instalment prediction model 114 using gradient boosting, that identifies customers who may take up instalment product purchases. As an example, the instalment prediction model 114 may be generated and trained using data mining and modeling services provided by external service provider such as Salford Systems as shown in the FIG.4A. However, this should not be considered as a limitation of the present disclosure, as any other service provider apart from Salford Systems may be used to generate and train the instalment prediction model 114 for identifying customers who may take up instalment product purchases. In some embodiments, the output of the instalment prediction model 114 may include, but not limited to, model score to target customers with high propensity for Easy Payment Plan (EPP) booking, in order to grow inorganic balances in the form of interest earned due to the EPP. In some embodiments, such an instalment prediction model 114 may be integrated with bank infrastructures in order to target the identified customers on a monthly or a weekly basis via Below-The-Line (BTL) channels like tele-calling, electronic Direct Mail (eDM) and Short Message Service (SMS), that in turn boosts the EPP bookings and improves inorganic balances. FIG.4B shows exemplary key features and model performance of an instalment prediction model 114 that enables identifying customers who are likely to buy products through instalment plans or in other words EPP plans, and increasing their spends through targeted recommendations, according to some principles of the present disclosure.

[0052] FIG.5A discloses a schematic diagram of a system for identifying customer attrition according to some principles of the present disclosure.

[0053] In FIG.5A, a schematic diagram of a system 500 shows a data acquisition server 102 a data preparing unit 104, a feature extraction unit 110, and a balance attrition model 116. The data acquisition server 102 may receive client data from one or more data sources (not shown in the FIG.5A) associated with the data acquisition server 102. For instance, the data acquisition server 102 may be a server associated with Visa that may already store client data collected by the Visa Net (also referred as Visa Net data). As an example, the Visa Net data may include, but not limited to, Issuer country, market segment, merchant name, source and destination amounts, plastic type, channel and the like. As an example, the one or more data sources associated with the data acquisition server 102 may include, but not limited to, an Issuer and any other external source that possesses and provides data required by the data acquisition server 102. As an example, the Issuer may be a bank that has issued a credit card for a user (also referred as customer). As an example, the client data provided by the Issuer may include, but not limited to, demographics such as income, age, nationality and the like, product holding and account details, Ending Net Receivable **(**ENR) balances, Repayment history, card Point of Sale (PoS) activity, merchant category spends and the like. As an example, the client data provided by the Issuer may also include bureau data that helps in establishing credit worthiness of the user. In some embodiments, the client data may be provided by each of the one or more data sources in a pre-defined format. Upon collecting the client data from the issuer, the data preparing unit 104 may prepare data for feature extraction. In some embodiments, key dimensions of data preparation used by the data preparing unit 104 may include, but not limited to, identifying historical cohorts of primary accounts of customers with all information, and an optimal indicator of attrition based on balance build behaviour. In some embodiments, to identify optimal indicator of attrition based on balance build behaviour, two main dimensions may include, but not limited to, time period over which balance behaviour should be analyzed and severity of definition. In some embodiments, each cohort of historical data is observed for subsequent ‘x’ months to determine balance behaviour relative to past patterns. For instance, increase in balance, balance drop (<10%, 10 –25%, 25-50%, 50-75%, 75-100%), and balance drop (>100%). In some embodiments, analysis of different definitions of balance drops in consecutive months to determine when a primary account holder can be termed as ‘balance attrite-d’.

[0054] In some embodiments, upon preparing the data based on the key dimensions as mentioned above, the feature extraction unit 110 may perform feature extraction using the client data received from the Issuer and the Visa Net data. As an example, the features extracted from the client data received from the Issuer and the Visa Net data may include, but not limited to, Demographics such as Income, Age, Nationality, MoB, segment and the like, product holding such as Account holding across Current Account Saving Account (CASA), loans and the like, Spend and Transaction Pattern such as recency, frequency, monetary value, consistency, diversity of spends and transactions, and the like, Balance and Payment History that identifies customer as a transactor or revolver, and the like. In some embodiments, more than thousand features may be derived using the client data provided by the issuer and the Visa Net data. Thereafter, the extracted features are used for building a balance attrition model 116 using gradient boosting, that controls spend leakage and customer churn. In other words, balance attrition model 116 helps in identifying customers who are moving to credit cards issued by other banks. As an example, the balance attrition model 116 may be generated and trained using data mining and modeling services provided by external service provider such as Salford Systems as shown in the FIG.5A. However, this should not be considered as a limitation of the present disclosure, as any other service provider apart from Salford Systems may be used to generate and train the balance attrition model 116 controls spend leakage and customer churn. In some embodiments, the output of the balance attrition model 116 may include, but not limited to, model score and policy parameter to create action segments to target retention efforts. In some embodiments, such a balance attrition model 116 may be integrated with bank infrastructures in order to target the identified customers on a monthly or a weekly basis, that in turn helps in monthly retention practice, thereby retaining customers of the bank. FIG.5B shows exemplary key features and model performance of balance attrition model 116 that enables identifying customers who are likely to attrite in a few months, and performing targeted actions to retain such customers, according to some principles of the present disclosure.

[0055] FIG. 6 discloses a schematic diagram of a system showing a solution that combines all solutions disclosed in the present disclosure together for finding optimal actions according to some principles of the present disclosure.

[0056] In FIG. 6, a schematic diagram of a system 600 shows that models built under FIG.1-FIG.5 as explained above are combined in order to build a strong, robust and comprehensive model that as features of all the models in a single model. For instance, the revolver model for acquisition of potential revolvers, hybrid marked recommender based on MLP for targeting right customers with right categories for deepening and diversifying the spends, revolve prediction model that identifies transactor who can be converted to potential revolvers or likely to get converted into revolvers in next few months, instalment prediction that identifies customers who may take up instalment product purchases, and balance attrition model that helps in identifying customers who are moving to credit cards issued by other banks may be combined together into one single solution. In some embodiments, using this multiple models combined into one single solution, the present disclosure initially clusters the customers exhibiting similar behaviour into clusters. As shown in the FIG.6, key dimensions integrated to create clusters of the customers exhibiting similar behaviour may include, but not limited to, category deepening that involves increasing spends of the customer in existing merchant categories where the customer spend is active, category diversification that involves increasing spends of the customer in new merchant categories where the customer is spend inactive, transactor to revolver propensity that involves identifying transactors who are likely to revolve in next few months, for example, 3 months, instalment product propensity that involves identifying transactors likely to take instalment product in next few months, for example, in next 3 months, and card utilization that involves computing spend and Ending Net Receivables (ENR) ratio as a percentage of credit limit. Based on the aforementioned key dimensions, a clustering model clusters the customers that exhibit a similar behaviour as shown in step 2 of the FIG.6. As an example, key clusters of customers that are generated as shown in the FIG.6 may include, but not limited to, Loyalists, Dormant, Precarious Passives, High Potentials, Prized Revolvers, and Engaged occasional revolvers. For instance, Loyalists may be the customers who loyally stick to the Issuer’s credit card network without getting subjected to attrition, Dormant may be those customers who own a credit card but are inactive, Precarious passives may be those customers who have minimal passive transactions, high potentials may be those customers who have a potential of spending on targeted products of interest, prized revolvers may be those customers who actively use credit cards and have continuously been revolvers, and occasional revolvers may be those customers who revolve only at times but most of the times clear the credit within the time limit. In some embodiments, the present disclosure is not limited to the aforementioned cluster groups, as there can be other cluster groups to broaden or narrow down the categorization of customers. Upon clustering, the solution may include targeting actions for each segment, in other words to each cluster of customers based on current engagement levels, card utilization, propensity to revolve/Easy Payment Plan (EPP) and risk of attrition. In some embodiments, the objective of targeted actions for each segment may be spend activation and proactive retention, to drive spends and grow balances, and to retain balances and increase loyalty as shown in the FIG.6.

[0057] In some embodiments, implementation of AI enabled credit card revenue maximizer solutions as discussed above have said to result in $91 million and $6 million incremental spend and revenue respectively for an issuer. The implementation of AI enabled credit card revenue maximizer solution strengthens issuer's credit card portfolio, optimizes customer value and also realizes benefits to the issuer, which in turn creates win-win situation for both customers and banks.

[0058] FIG.7 discloses a schematic diagram of an architecture showing an Ending Net Receivables (ENR) scoring and optimization engine according to some principles of the present disclosure.

[0059] As shown in the FIG.7, the architecture 700 may include a data ingestion and validation section, a Machine Learning (ML) compute engine/service section and a data monetization marketplace segment. In the data ingestion and validation section, a data acquisition server 102 receives client data from one or more data sources (not shown in the FIG.7) associated with the data acquisition server 102. For instance, the data acquisition server 102 may be a server associated with Visa that may already store client data collected by the Visa Net (also referred as Visa Net data). As an example, the Visa Net data may include, but not limited to, Issuer country, market segment, merchant name, source and destination amounts, plastic type, channel and the like. As an example, the one or more data sources associated with the data acquisition server 102 may include, but not limited to, an Issuer and any other external source that possesses and provides data required by the data acquisition server 102. As an example, the Issuer may be a bank that has issued a credit card for a user (also referred as customer). As an example, the client data provided by the Issuer may include, but not limited to, demographics such as income, age, nationality and the like, product holding and account details, Ending Net Receivable **(**ENR) balances, Repayment history, card Point of Sale (PoS) activity, merchant category spends and the like. As an example, the client data provided by the Issuer may also include bureau data that helps in establishing credit worthiness of the user. In some embodiments, the client data may be provided by each of the one or more data sources in a pre-defined format. Upon collecting the client data from the issuer, the Visa Net data and the client data collected from the issuer may be sent to a data validator for validating correctness of the data. Thereafter, as part of the ML compute engine/service segment, an appropriate/suitable model based on requirement is select to ensure relevant model run and the validated data is subjected through that model. In some embodiments, batch scoring/prediction and/or real-time scoring/prediction using Artificial Intelligence Platform (AIP) may be performed on the data of various customers in order to perform a targeted action as per the prediction, as part of the data monetization marketplace segment shown in the FIG.7. Such predictions and score maybe provided to the partner banks in order to perform targeted marketing and increase credit card-based interest revenue.

[0060] FIG.8 shows an exemplary PyModel deployment for using Jupyter® as service used for preparing data for performing feature extraction and model building, according to some principles of the present disclosure. FIG.9 shows an exemplary PyModel deployment for using Machine Learning (ML) service for generating batch predictions and real-time predictions, according to some principles of the present disclosure. FIG.10 shows an exemplary PyModel deployment for using Representational State Transfer (REST) Application Programming Interface (API) for communicating with the Artificial Intelligence Platform (AIP), according to some principles of the present disclosure. FIG.11 shows an exemplary PyModel for building and training models using Multi Layer Perceptron (MLP), according to some principles of the present disclosure.

[0061] FIG. 12 shows a flowchart that illustrates a method 1200 for Artificial Intelligence (AI) enabled credit card revenue maximizer, according to a non-limiting embodiment.

[0062] As illustrated in FIG. 12, the method 1200 comprises one or more blocks implemented for maximizing credit card revenue. The method 1200 may be described in the general context of computer executable instructions. Generally, computer executable instructions can include routines, programs, objects, components, data structures, procedures, modules, and functions, which perform specific functions or implement specific abstract data types.

[0063] The order in which the method 1200 is described is not intended to be construed as a limitation, and any number of the described method blocks can be combined in any order to implement the method. Additionally, individual blocks may be deleted from the methods without departing from the spirit and scope of the subject matter described herein. Furthermore, the method can be implemented in any suitable hardware, software, firmware, or combination thereof.

[0064] The steps of the method shown may be carried out by one or more processors of an AI based system for maximizing credit card revenue. At block 1201, the processor receives client data from one or more data sources such as Issuer bank, Visa Net and any other external source that has client data. Further, the processor also receives bureau data that helps in establishing credit worthiness of a customer. At block 1203, the processor prepares the received data based on key dimensions as per the requirement. For instance, when the requirement is identifying transactors who are likely to convert into revolvers in a few months, the key dimensions with respect to the revolver prediction model may be used for data preparation. At block 1205, features extraction is performed based on the requirement, using the data prepared at block 1203. At block 1207, an AI based model relevant to the requirement is selected and the extracted features are provided as input to the selected AI based model for generating predictions. For instance, when the requirement is identifying transactors who are likely to convert into revolvers in a few months, then the AI based model selected for generating predictions may be a revolver prediction model. Similarly, when the requirement is identifying customers who are likely to opt installment loan plans, then the AI based model selected for generating predictions may be an instalment prediction model. At block 1209, the generated predictions are provided to a partner issuer bank, in order to target customized recommendations based on the predictions to the customer and enhancing the credit card revenue.

[0065] FIG. 13 is a block diagram of an exemplary computer system for implementing embodiments consistent with the present disclosure.

[0066] In some embodiments, FIG. 13 illustrates a block diagram of an exemplary computer system 1300 for implementing embodiments consistent with the present disclosure. In some embodiments, the computer system 1300 may include a central processing unit (“CPU” or “processor”) 1302 that is associated with one or more Artificial Intelligence (AI) based models disclosed in the present disclosure to perform the method of maximizing credit card revenue. The processor 1302 may include at least one data processor for executing program components for executing user or system-generated business processes. A user may include a person, a person using a device such as those included in this disclosure, or such a device itself. The processor 1302 may include specialized processing units such as integrated system (bus) controllers, memory management control units, floating point units, graphics processing units, digital signal processing units, etc.

[0067] The processor 1302 may be disposed in communication with input devices 1311 and output devices 1312 via I/O interface 1301. The I/O interface 1301 may employ communication protocols/methods such as, without limitation, audio, analog, digital, stereo, IEEE-1393, serial bus, Universal Serial Bus (USB), infrared, PS/2, BNC, coaxial, component, composite, Digital Visual Interface (DVI), high-definition multimedia interface (HDMI), Radio Frequency (RF) antennas, S-Video, Video Graphics Array (VGA), IEEE 802.n /b/g/n/x, Bluetooth, cellular (e.g., Code-Division Multiple Access (CDMA), High-Speed Packet Access (HSPA+), Global System For Mobile Communications (GSM), Long-Term Evolution (LTE), WiMax, or the like), etc.

[0068] Using the I/O interface 1301, the computer system 1300 may communicate with the input devices 1311 and the output devices 1312.

[0069] In some embodiments, the processor 1302 may be disposed in communication with a communication network 1309 via a network interface 1303. The network interface 1303 may communicate with the communication network 1309. The network interface 1303 may employ connection protocols including, without limitation, direct connect, Ethernet (e.g., twisted pair 10/100/1000 Base T), Transmission Control Protocol/Internet Protocol (TCP/IP), token ring, IEEE

802.11a/b/g/n/x, etc. Using the network interface 1303 and the communication network 1309, the computer system 1300 may communicate with data source 1313_1 to data source 1313_n (also referred as one or more data sources 1313). As an example, the one or more data sources 1313 may include an issuer bank and any other external source comprising client data. The communication network 1309 can be implemented as one of the different types of networks, such as intranet or Local Area Network (LAN), Closed Area Network (CAN) and such. The communication network 1309 may either be a dedicated network or a shared network, which represents an association of the different types of networks that use a variety of protocols, for example, Hypertext Transfer Protocol (HTTP), CAN Protocol, Transmission Control Protocol/Internet Protocol (TCP/IP), Wireless Application Protocol (WAP), etc., to communicate with each other. Further, the communication network 1309 may include a variety of network devices, including routers, bridges, servers, computing devices, storage devices, etc. In some embodiments, the processor 1302 may be disposed in communication with a memory 1305 (e.g., RAM, ROM, etc. not shown in FIG.3) via a storage interface 1303. The storage interface 1303 may connect to memory 1305 including, without limitation, memory drives, removable disc drives, etc., employing connection protocols such as Serial Advanced Technology Attachment (SATA), Integrated Drive Electronics (IDE), IEEE-1393, Universal Serial Bus (USB), fibre channel, Small Computer Systems Interface (SCSI), etc. The memory drives may further include a drum, magnetic disc drive, magneto-optical drive, optical drive, Redundant Array of Independent Discs (RAID), solid-state memory devices, solid-state drives, etc.

[0070] The memory 1305 may store a collection of program or database components, including, without limitation, a user interface 1306, an operating system 1307, a web browser 1308 etc. In some embodiments, the computer system 1300 may store user/application data, such as the data, variables, records, etc. as described in this disclosure. Such databases may be implemented as fault-tolerant, relational, scalable, secure databases such as Oracle or Sybase.

[0071] The operating system 1307 may facilitate resource management and operation of the computer system 1300. Examples of operating systems include, without limitation, APPLE® MACINTOSH® OS X®, UNIX®, UNIX-like system distributions (E.G., BERKELEY SOFTWARE DISTRIBUTION® (BSD), FREEBSD®, NETBSD®, OPENBSD, etc.), LINUX® DISTRIBUTIONS (E.G., RED HAT®, UBUNTU®, KUBUNTU®, etc.), IBM®OS/2®,

MICROSOFT® WINDOWS® (XP®, VISTA®/7/8, 10 etc.), APPLE® IOS®, GOOGLE™ ANDROID™, BLACKBERRY® OS, or the like. The User interface 1306 may facilitate display, execution, interaction, manipulation, or operation of program components through textual or graphical facilities. For example, user interfaces may provide computer interaction interface elements on a display system operatively connected to the computer system 1300, such as cursors, icons, checkboxes, menus, scrollers, windows, widgets, etc. Graphical User Interfaces (GUIs) may be employed, including, without limitation, Apple® Macintosh® operating systems' Aqua®, IBM® OS/2®, Microsoft® Windows® (e.g., Aero, Metro, etc.), web interface libraries (e.g., ActiveX®, Java®, Javascript®, AJAX, HTML, Adobe® Flash®, etc.), or the like.

[0072] In some embodiments, the computer system 1300 may implement the web browser 1308 stored program components. The web browser 1308 may be a hypertext viewing application, such as MICROSOFT® INTERNET EXPLORER®, GOOGLE™ CHROME™, MOZILLA® FIREFOX®, APPLE® SAFARI®, etc. Secure web browsing may be provided using Secure Hypertext Transport Protocol (HTTPS), Secure Sockets Layer (SSL), Transport Layer Security (TLS), etc. Web browsers 1308 may utilize facilities such as AJAX, DHTML, ADOBE® FLASH®, JAVASCRIPT®, JAVA®, Application Programming Interfaces (APIs), etc. In some embodiments, the computer system 1300 may implement a mail server stored program component. The mail server may be an Internet mail server such as Microsoft Exchange, or the like. The mail server may utilize facilities such as Active Server Pages (ASP), ACTIVEX®, ANSI® C++/C#, MICROSOFT®, .NET, CGI SCRIPTS, JAVA®, JAVASCRIPT®, PERL®, PHP, PYTHON®, WEBOBJECTS®, etc. The mail server may utilize communication protocols such as Internet Message Access Protocol (IMAP), Messaging Application Programming Interface (MAPI), MICROSOFT® exchange, Post Office Protocol (POP), Simple Mail Transfer Protocol (SMTP), or the like. In some embodiments, the computer system 1300 may implement a mail client stored program component. The mail client may be a mail viewing application, such as APPLE® MAIL, MICROSOFT® ENTOURAGE®, MICROSOFT® OUTLOOK®, MOZILLA® THUNDERBIRD®, etc.

[0073] Furthermore, one or more computer-readable storage media may be utilized in implementing embodiments consistent with the present disclosure. A computer-readable storage medium refers to any type of physical memory on which information or data readable by a processor may be stored. Thus, a computer-readable storage medium may store instructions for execution by one or more processors, including instructions for causing the processor(s) to perform steps or stages consistent with the embodiments described herein. The term "computer-readable medium" should be understood to include tangible items and exclude carrier waves and transient signals, i.e., non-transitory. Examples include Random Access Memory (RAM), Read-Only Memory (ROM), volatile memory, non-volatile memory, hard drives, Compact Disc (CD) ROMs, Digital Video Disc (DVDs), flash drives, disks, and any other known physical storage media.

[0074] Finally, the language used in the specification has been principally selected for readability and instructional purposes, and it may not have been selected to delineate or circumscribe the inventive subject matter. Accordingly, the disclosure of the embodiments of the disclosure is intended to be illustrative, but not limiting, of the scope of the disclosure.

[0075] With respect to the use of substantially any plural and/or singular terms herein, those having skill in the art can translate from the plural to the singular and/or from the singular to the plural as is appropriate to the context and/or application. The various singular/plural permutations may be expressly set forth herein for sake of clarity.

[0076] Although the invention has been described in detail for the purpose of illustration based on what is currently considered to be the most practical and preferred embodiments, it is to be understood that such detail is solely for that purpose and that the invention is not limited to the disclosed embodiments, but, on the contrary, is intended to cover modifications and equivalent arrangements that are within the spirit and scope of the appended claims. For example, it is to be understood that the present invention contemplates that, to the extent possible, one or more features of any embodiment can be combined with one or more features of any other embodiment.

ARTIFICIAL INTELLIGENCE (AI) BASED METHODS AND SYSTEMS FOR MAXIMIZING CREDIT CARD REVENUE

ABSTRACT

The present disclosure is related to field of Artificial Intelligence (AI) and finance that provides AI based methods and systems for maximizing credit card revenue. The objective of the methods and systems disclosed in the present disclosure is to induce spending by personalizing offers and communications that are tailored towards customer need, identifying potential revolvers in the credit card portfolio to give them right line of credit and treatment to enrich their revolving experience, build portfolio balance through installment loan sell and proactively, identifying potential attritors and stop the portfolio leakage. To achieve the aforementioned objectives, the claimed invention provides a hybrid market recommender for personalizing offers and communications, revolve prediction model for identifying revolving behaviour, instalment prediction model for identifying installment loan takers, balance attrition model for identifying potential customer leakage, and heavy machine learning models for predictive model development. Further, the present disclosure also provides an all in one robust and comprehensive solution that is a combination of all the aforementioned models and provide targeted recommendations to a group of similar customers.

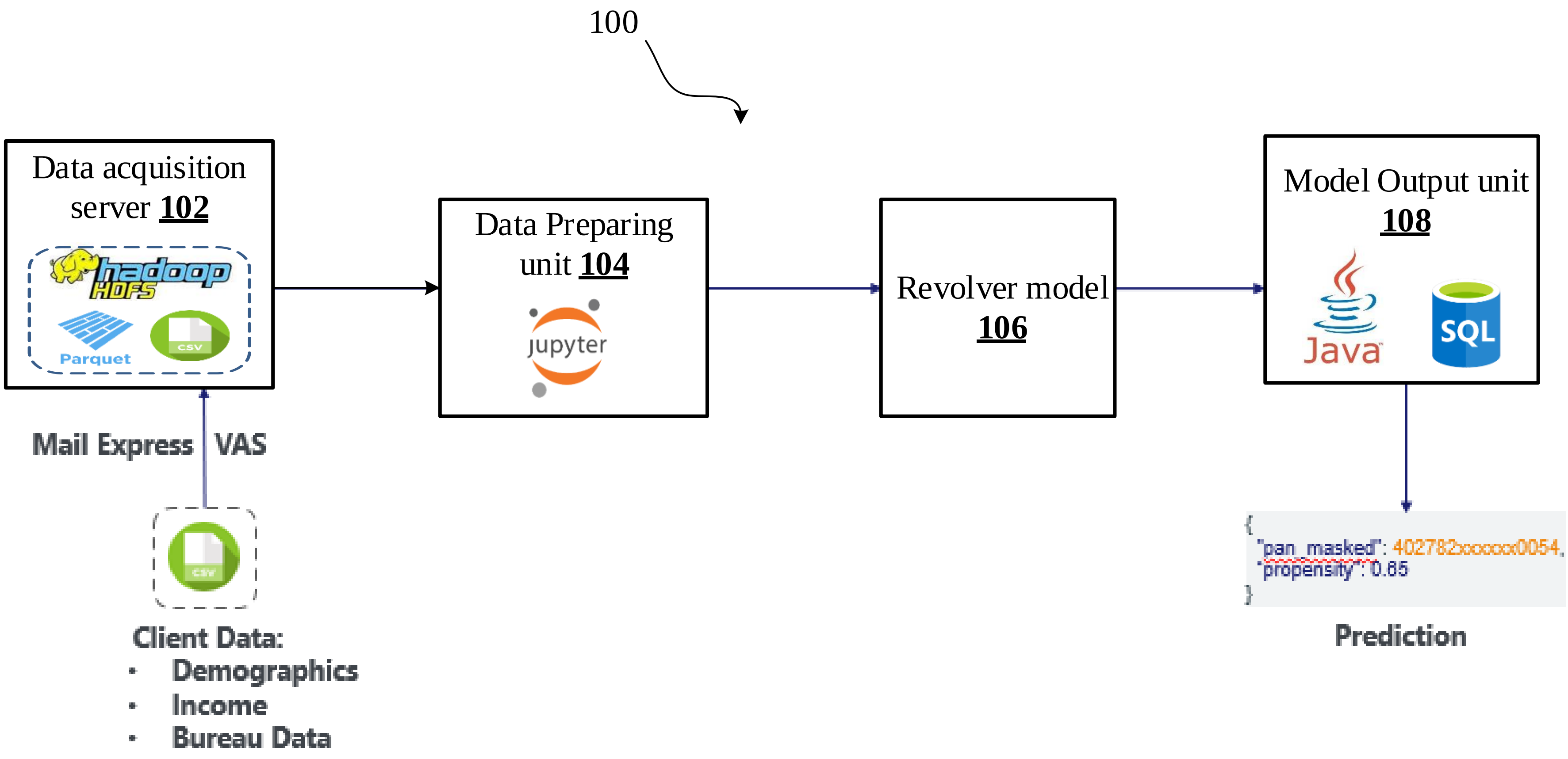
100
Data acquisition server 102
hadoop HDFS
Parquet
CSV
Data Preparing unit 104
jupyter
Revolver model 106
Model Output unit 108
Java
SQL
Mail Express
VAS
CSV
Client Data:
• Demographics
• Income
• Bureau Data
{
"pan_masked": 402782xxxxxx0054,
"propensity": 0.85
}
Prediction

FIGURE 1A

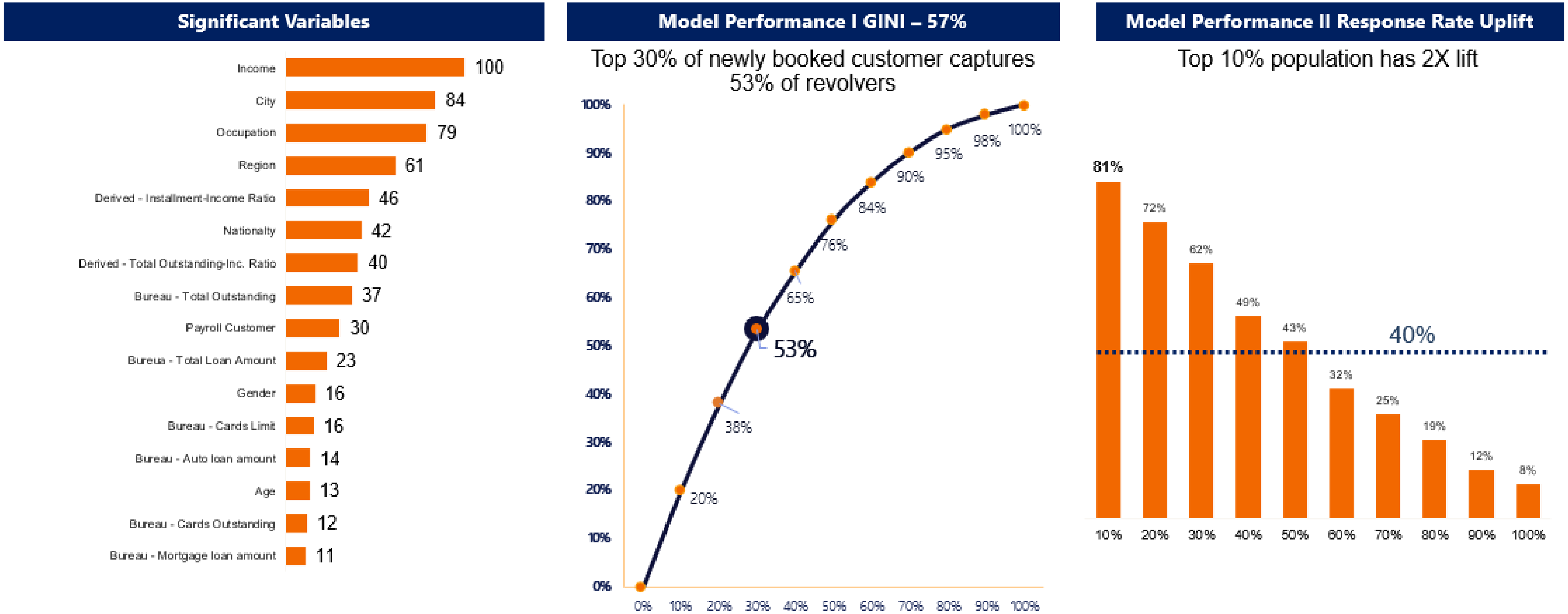
Significant Variables
Income 100
City 84
Occupation 79
Region 61
Derived - Installment-Income Ratio 46
Nationalty 42
Derived - Total Outstanding-Inc. Ratio 40
Bureau - Total Outstanding 37
Payroll Customer 30
Bureua - Total Loan Amount 23
Gender 16
Bureau - Cards Limit 16
Bureau - Auto loan amount 14
Age 13
Bureau - Cards Outstanding 12
Bureau - Mortgage loan amount 11
Model Performance I GINI – 57%
Top 30% of newly booked customer captures 53% of revolvers
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
20%
38%
53%
65%
76%
84%
90%
95%
98%
100%
0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%
Model Performance II Response Rate Uplift
Top 10% population has 2X lift
81%
72%
62%
49%
43%
40%
32%
25%
19%
12%
8%
10% 20% 30% 40% 50% 60% 70% 80% 90% 100%

FIGURE 1B

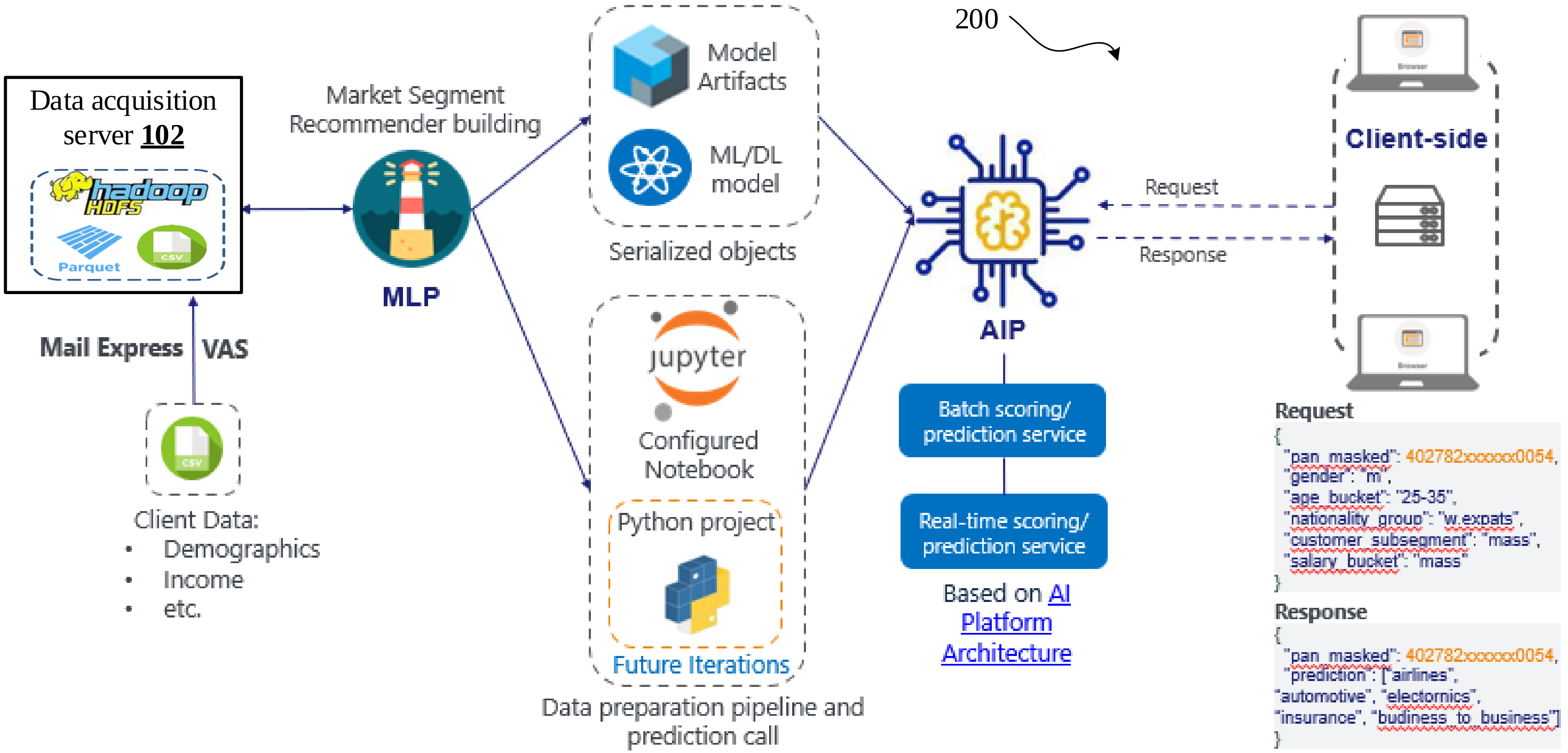
200
Data acquisition server 102
hadoop HDFS
Parquet
CSV
Market Segment Recommender building
MLP
Mail Express
VAS
Client Data:
• Demographics
• Income
• etc.
Model Artifacts
ML/DL model
Serialized objects
jupyter
Configured Notebook
Python project
Future Iterations
Data preparation pipeline and prediction call
AIP
Batch scoring/ prediction service
Real-time scoring/ prediction service
Based on AI Platform Architecture
Request
Response
Client-side
Request
{
"pan_masked": 402782xxxxxx0054,
"gender": "m",
"age_bucket": "25-35",
"nationality_group": "w.expats",
"customer_subsegment": "mass",
"salary_bucket": "mass"
}
Response
{
"pan_masked": 402782xxxxxx0054,
"prediction": ["airlines",
"automotive", "electornics",
"insurance", "budiness_to_business"]
}

FIGURE 2A

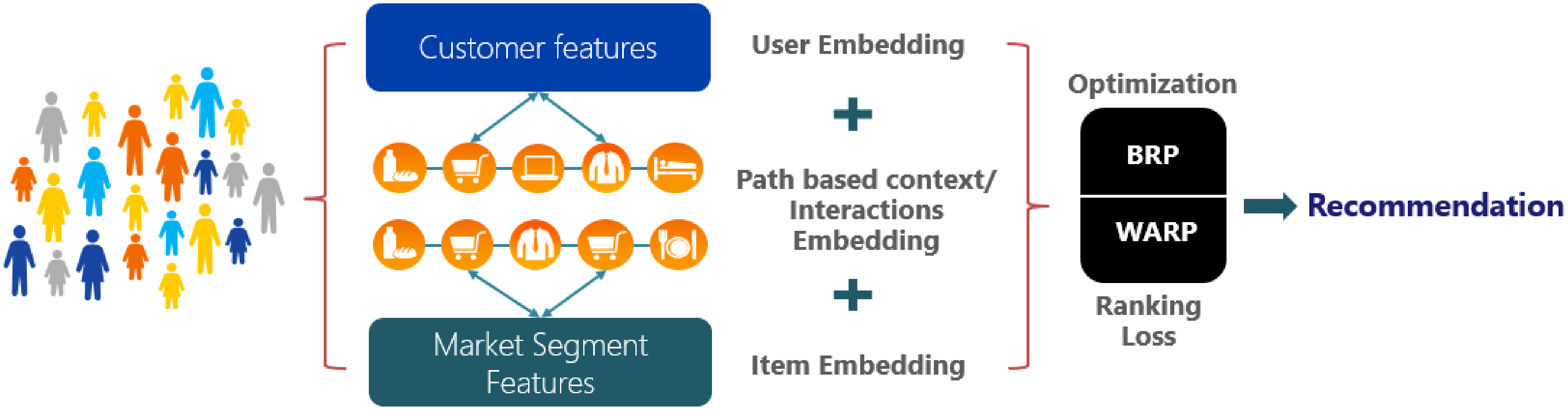
Customer features
User Embedding
Path based context/
Interactions
Embedding
Market Segment
Features
Item Embedding
Optimization
BRP
WARP
Ranking
Loss
Recommendation

FIGURE 2B

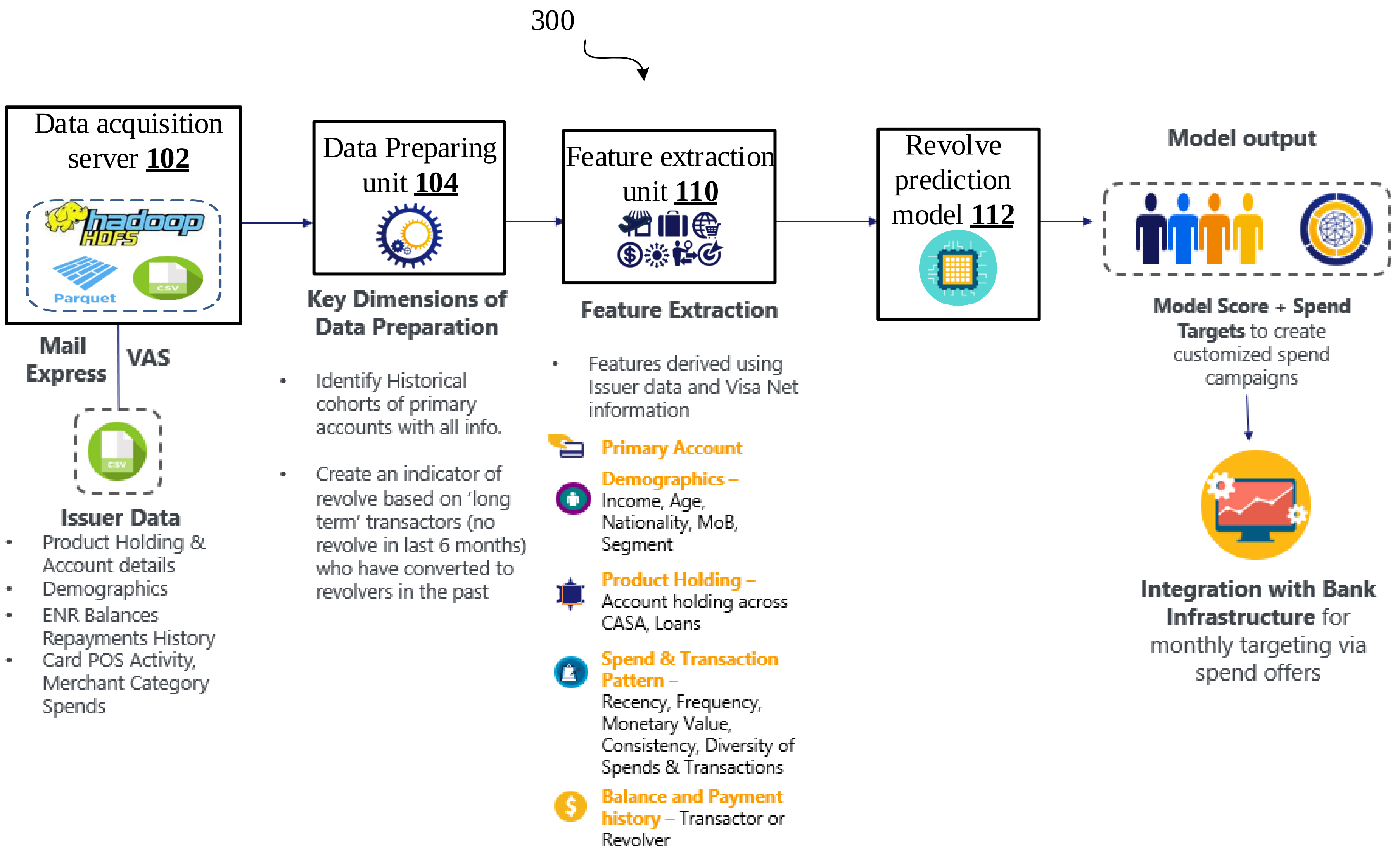
300
Data acquisition server 102
hadoop HDFS
Parquet
CSV
Mail Express
VAS
CSV
Issuer Data
• Product Holding & Account details
• Demographics
• ENR Balances Repayments History
• Card POS Activity, Merchant Category Spends
Data Preparing unit 104
Key Dimensions of Data Preparation
• Identify Historical cohorts of primary accounts with all info.
• Create an indicator of revolve based on 'long term' transactors (no revolve in last 6 months) who have converted to revolvers in the past
Feature extraction unit 110
Feature Extraction
• Features derived using Issuer data and Visa Net information
Primary Account
Demographics – Income, Age, Nationality, MoB, Segment
Product Holding – Account holding across CASA, Loans
Spend & Transaction Pattern – Recency, Frequency, Monetary Value, Consistency, Diversity of Spends & Transactions
Balance and Payment history – Transactor or Revolver
Revolve prediction model 112
Model output
Model Score + Spend Targets to create customized spend campaigns
Integration with Bank Infrastructure for monthly targeting via spend offers

FIGURE 3A

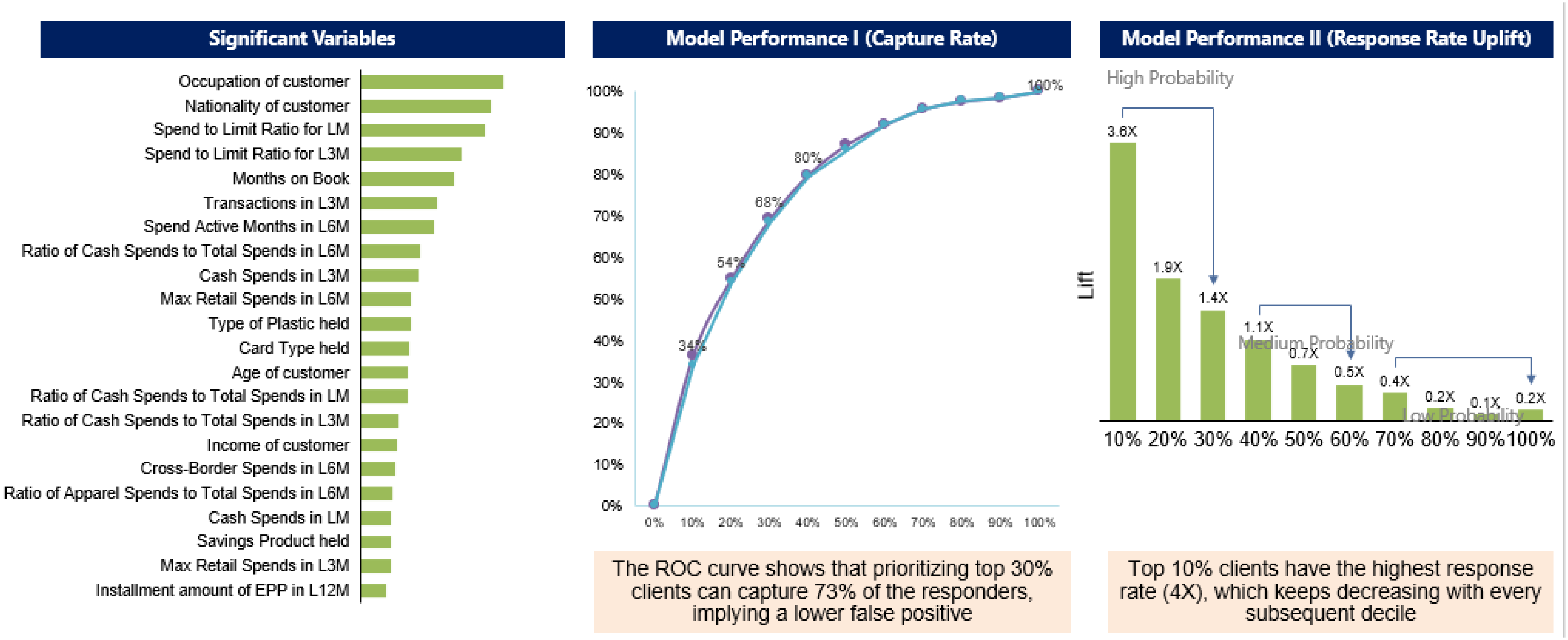
Significant Variables
Occupation of customer
Nationality of customer
Spend to Limit Ratio for LM
Spend to Limit Ratio for L3M
Months on Book
Transactions in L3M
Spend Active Months in L6M
Ratio of Cash Spends to Total Spends in L6M
Cash Spends in L3M
Max Retail Spends in L6M
Type of Plastic held
Card Type held
Age of customer
Ratio of Cash Spends to Total Spends in LM
Ratio of Cash Spends to Total Spends in L3M
Income of customer
Cross-Border Spends in L6M
Ratio of Apparel Spends to Total Spends in L6M
Cash Spends in LM
Savings Product held
Max Retail Spends in L3M
Installment amount of EPP in L12M
Model Performance I (Capture Rate)
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%
34%
54%
68%
80%
100%
The ROC curve shows that prioritizing top 30% clients can capture 73% of the responders, implying a lower false positive
Model Performance II (Response Rate Uplift)
High Probability
Medium Probability
Low Probability
Lift
3.6X
1.9X
1.4X
1.1X
0.7X
0.5X
0.4X
0.2X
0.1X
0.2X
10% 20% 30% 40% 50% 60% 70% 80% 90% 100%
Top 10% clients have the highest response rate (4X), which keeps decreasing with every subsequent decile

FIGURE 3B

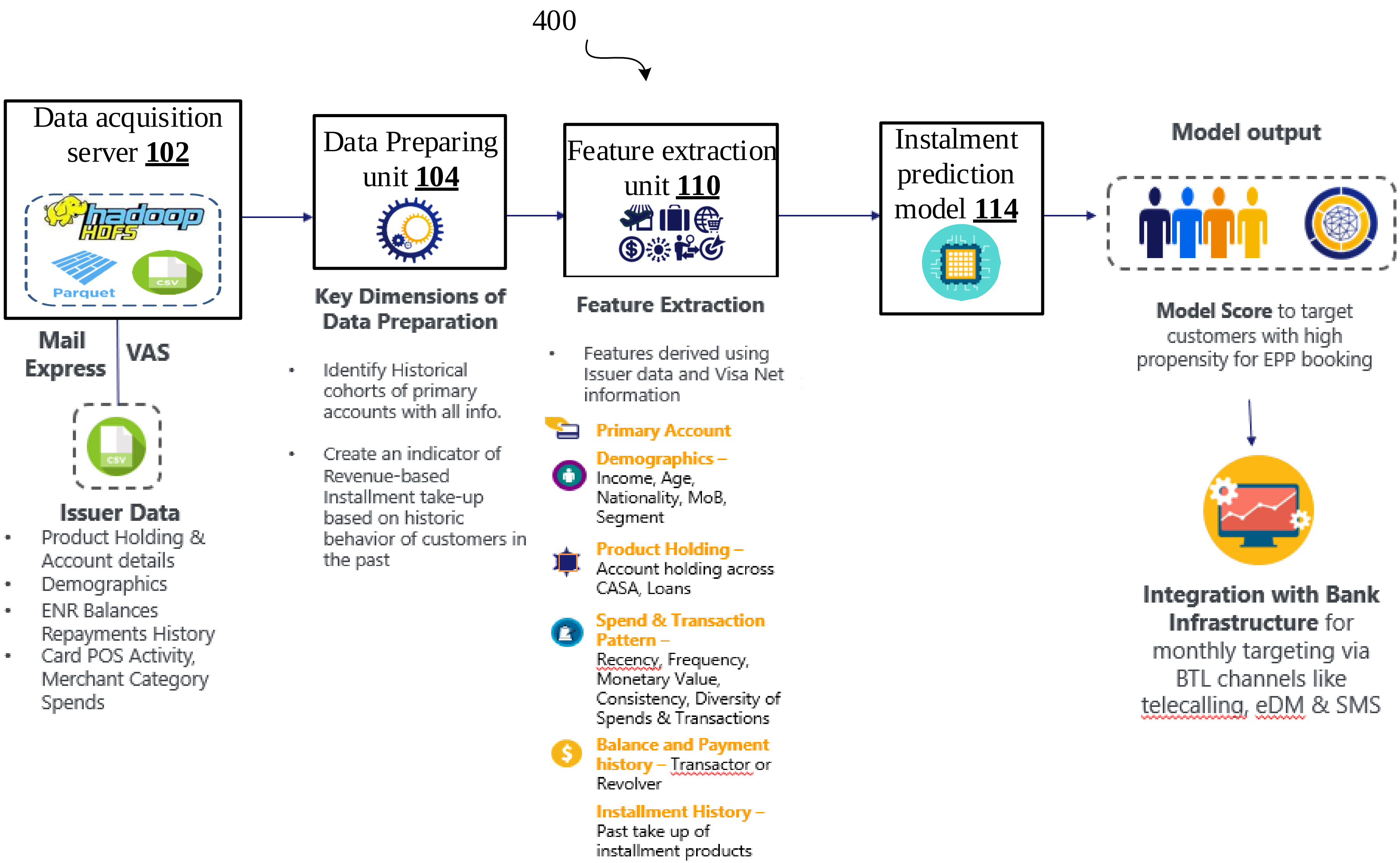
400
Data acquisition server 102
hadoop HDFS
Parquet
CSV
Mail Express
VAS
CSV
Issuer Data
• Product Holding & Account details
• Demographics
• ENR Balances Repayments History
• Card POS Activity, Merchant Category Spends
Data Preparing unit 104
Key Dimensions of Data Preparation
• Identify Historical cohorts of primary accounts with all info.
• Create an indicator of Revenue-based Installment take-up based on historic behavior of customers in the past
Feature extraction unit 110
Feature Extraction
• Features derived using Issuer data and Visa Net information
Primary Account
Demographics – Income, Age, Nationality, MoB, Segment
Product Holding – Account holding across CASA, Loans
Spend & Transaction Pattern – Recency, Frequency, Monetary Value, Consistency, Diversity of Spends & Transactions
Balance and Payment history – Transactor or Revolver
Installment History – Past take up of installment products
Instalment prediction model 114
Model output
Model Score to target customers with high propensity for EPP booking
Integration with Bank Infrastructure for monthly targeting via BTL channels like telecalling, eDM & SMS

FIGURE 4A

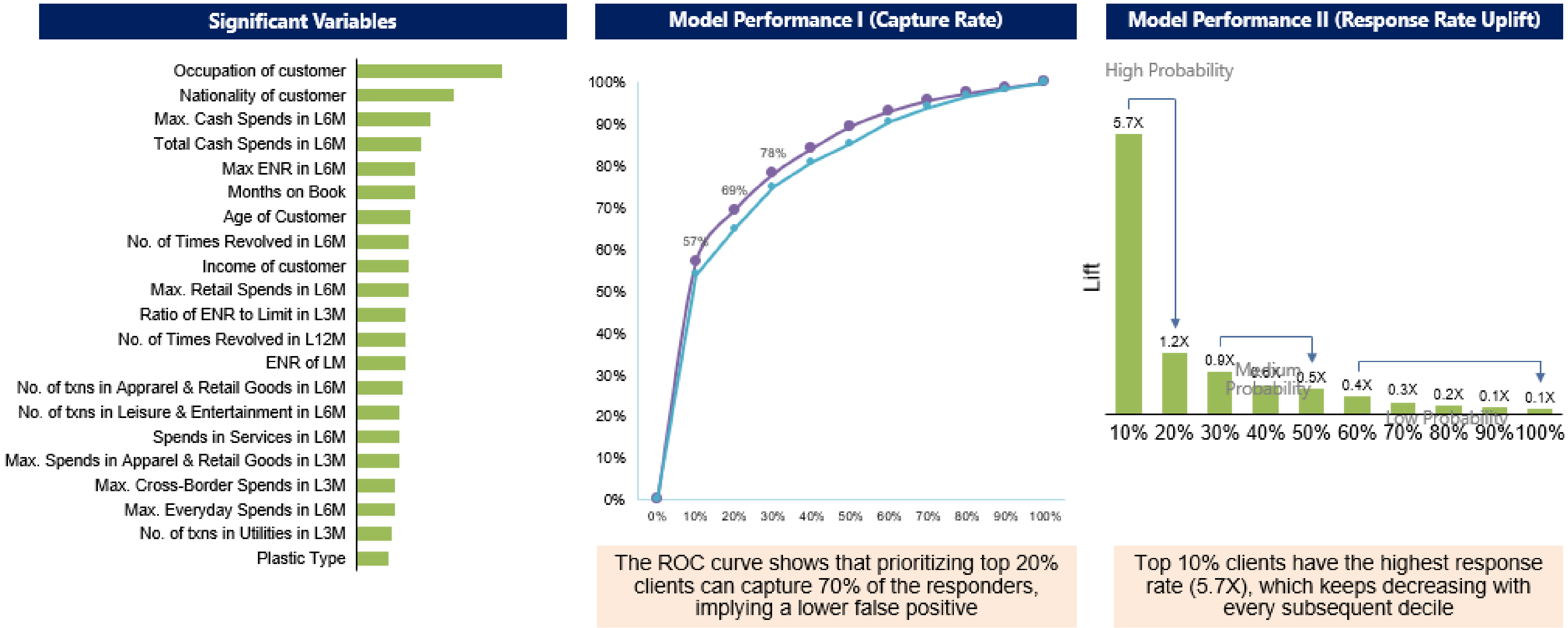
Significant Variables
Occupation of customer
Nationality of customer
Max. Cash Spends in L6M
Total Cash Spends in L6M
Max ENR in L6M
Months on Book
Age of Customer
No. of Times Revolved in L6M
Income of customer
Max. Retail Spends in L6M
Ratio of ENR to Limit in L3M
No. of Times Revolved in L12M
ENR of LM
No. of txns in Apprarel & Retail Goods in L6M
No. of txns in Leisure & Entertainment in L6M
Spends in Services in L6M
Max. Spends in Apparel & Retail Goods in L3M
Max. Cross-Border Spends in L3M
Max. Everyday Spends in L6M
No. of txns in Utilities in L3M
Plastic Type
Model Performance I (Capture Rate)
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
57%
69%
78%
0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%
The ROC curve shows that prioritizing top 20% clients can capture 70% of the responders, implying a lower false positive
Model Performance II (Response Rate Uplift)
High Probability
Lift
5.7X
1.2X
0.9X
0.6X
0.5X
0.4X
0.3X
0.2X
0.1X
0.1X
Medium Probability
Low Probability
10% 20% 30% 40% 50% 60% 70% 80% 90% 100%
Top 10% clients have the highest response rate (5.7X), which keeps decreasing with every subsequent decile

FIGURE 4B

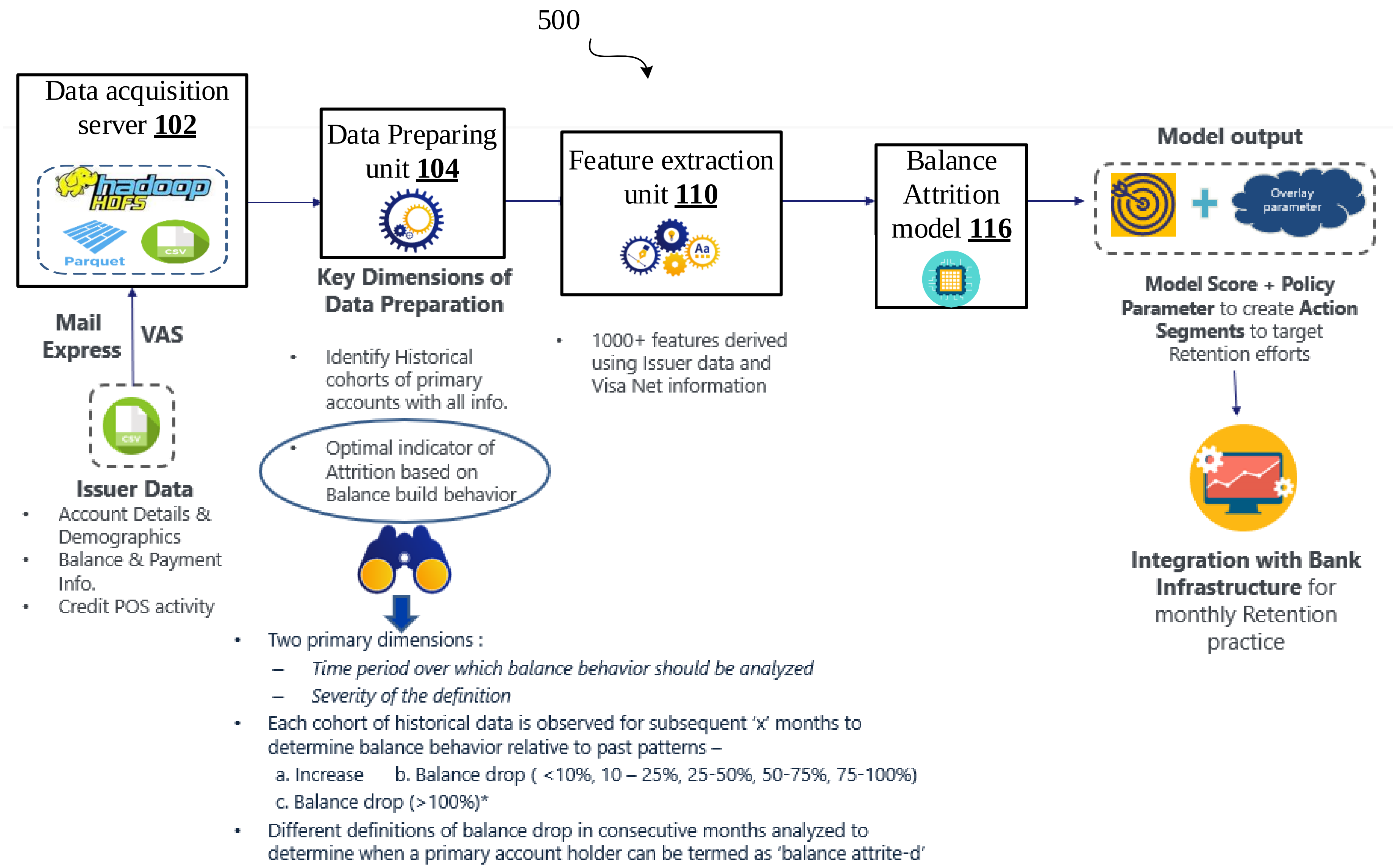
500
Data acquisition server 102
hadoop HDFS
Parquet
CSV
Data Preparing unit 104
Feature extraction unit 110
Balance Attrition model 116
Model output
Overlay parameter
Model Score + Policy Parameter to create Action Segments to target Retention efforts
Mail Express
VAS
Issuer Data
• Account Details & Demographics
• Balance & Payment Info.
• Credit POS activity
Key Dimensions of Data Preparation
• Identify Historical cohorts of primary accounts with all info.
• Optimal indicator of Attrition based on Balance build behavior
• 1000+ features derived using Issuer data and Visa Net information
Integration with Bank Infrastructure for monthly Retention practice
• Two primary dimensions :
– Time period over which balance behavior should be analyzed
– Severity of the definition
• Each cohort of historical data is observed for subsequent 'x' months to determine balance behavior relative to past patterns –
a. Increase b. Balance drop (<10%, 10 – 25%, 25-50%, 50-75%, 75-100%)
c. Balance drop (>100%)*
• Different definitions of balance drop in consecutive months analyzed to determine when a primary account holder can be termed as 'balance attrite-d'

FIGURE 5A

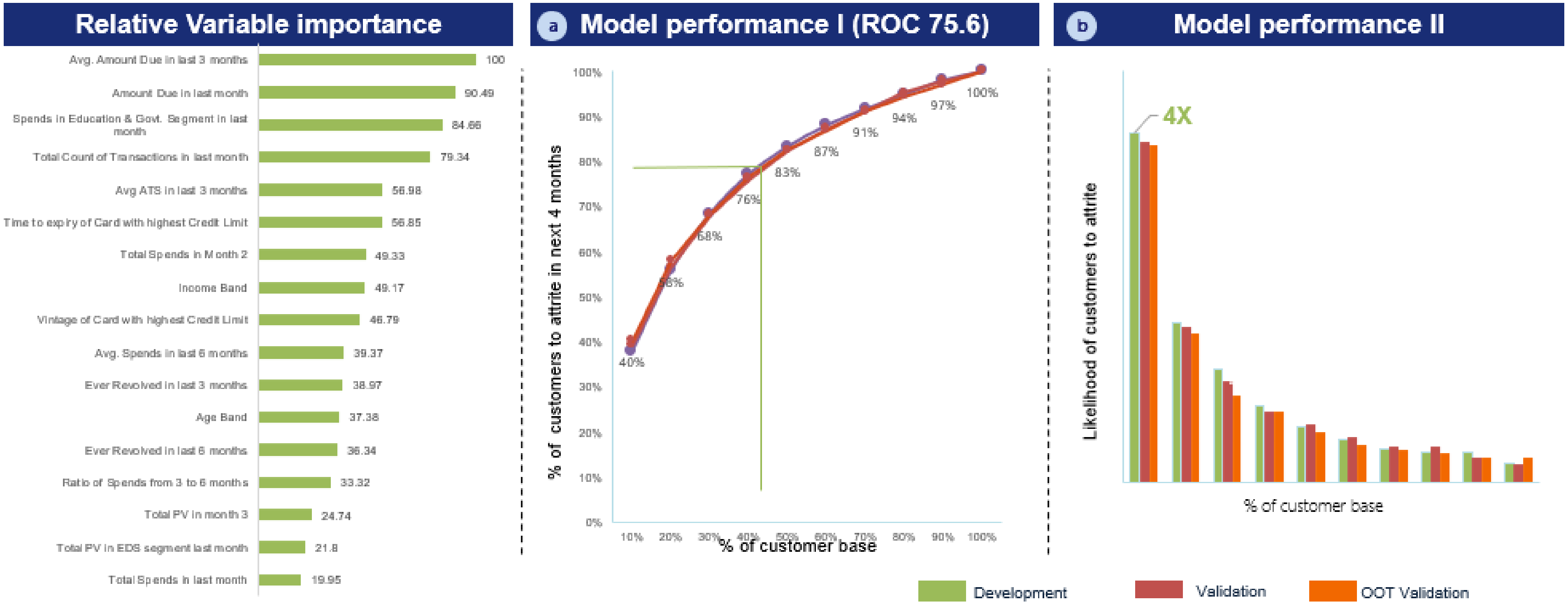
Relative Variable importance
Avg. Amount Due in last 3 months 100
Amount Due in last month 90.49
Spends in Education & Govt. Segment in last month 84.66
Total Count of Transactions in last month 79.34
Avg ATS in last 3 months 56.98
Time to expiry of Card with highest Credit Limit 56.85
Total Spends in Month 2 49.33
Income Band 49.17
Vintage of Card with highest Credit Limit 46.79
Avg. Spends in last 6 months 39.37
Ever Revolved in last 3 months 38.97
Age Band 37.38
Ever Revolved in last 6 months 36.34
Ratio of Spends from 3 to 6 months 33.32
Total PV in month 3 24.74
Total PV in EDS segment last month 21.8
Total Spends in last month 19.95
a Model performance I (ROC 75.6)
% of customers to attrite in next 4 months
% of customer base
40% 56% 68% 76% 83% 87% 91% 94% 97% 100%
b Model performance II
Likelihood of customers to attrite
% of customer base
4X
Development
Validation
OOT Validation

FIGURE 5B

600

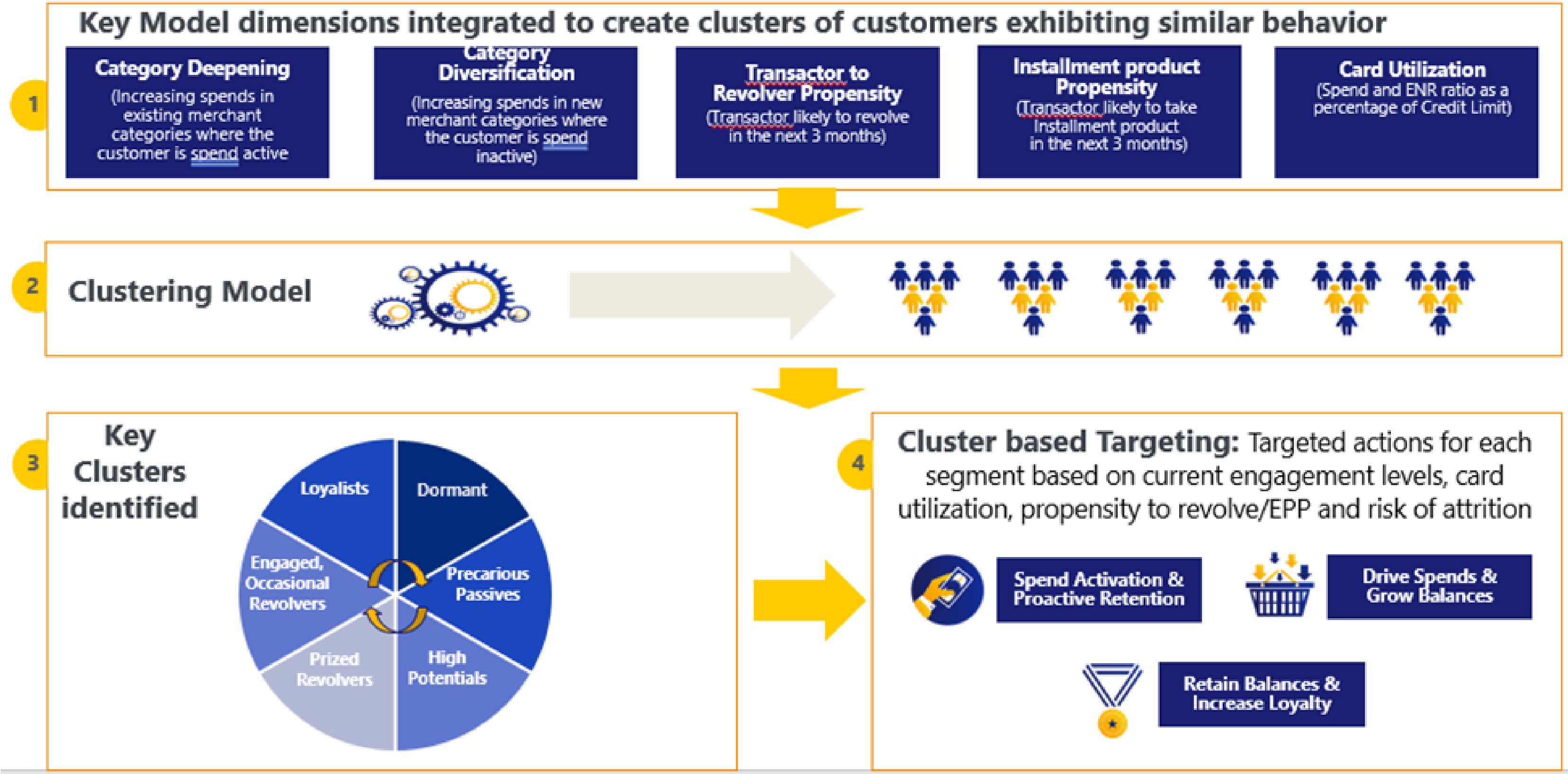
Key Model dimensions integrated to create clusters of customers exhibiting similar behavior
1
Category Deepening
(Increasing spends in existing merchant categories where the customer is spend active
Category Diversification
(Increasing spends in new merchant categories where the customer is spend inactive)
Transactor to Revolver Propensity
(Transactor likely to revolve in the next 3 months)
Installment product Propensity
(Transactor likely to take Installment product in the next 3 months)
Card Utilization
(Spend and ENR ratio as a percentage of Credit Limit)
2
Clustering Model
3
Key Clusters identified
Loyalists
Dormant
Engaged, Occasional Revolvers
Precarious Passives
Prized Revolvers
High Potentials
4
Cluster based Targeting: Targeted actions for each segment based on current engagement levels, card utilization, propensity to revolve/EPP and risk of attrition
Spend Activation & Proactive Retention
Drive Spends & Grow Balances
Retain Balances & Increase Loyalty

FIGURE 6

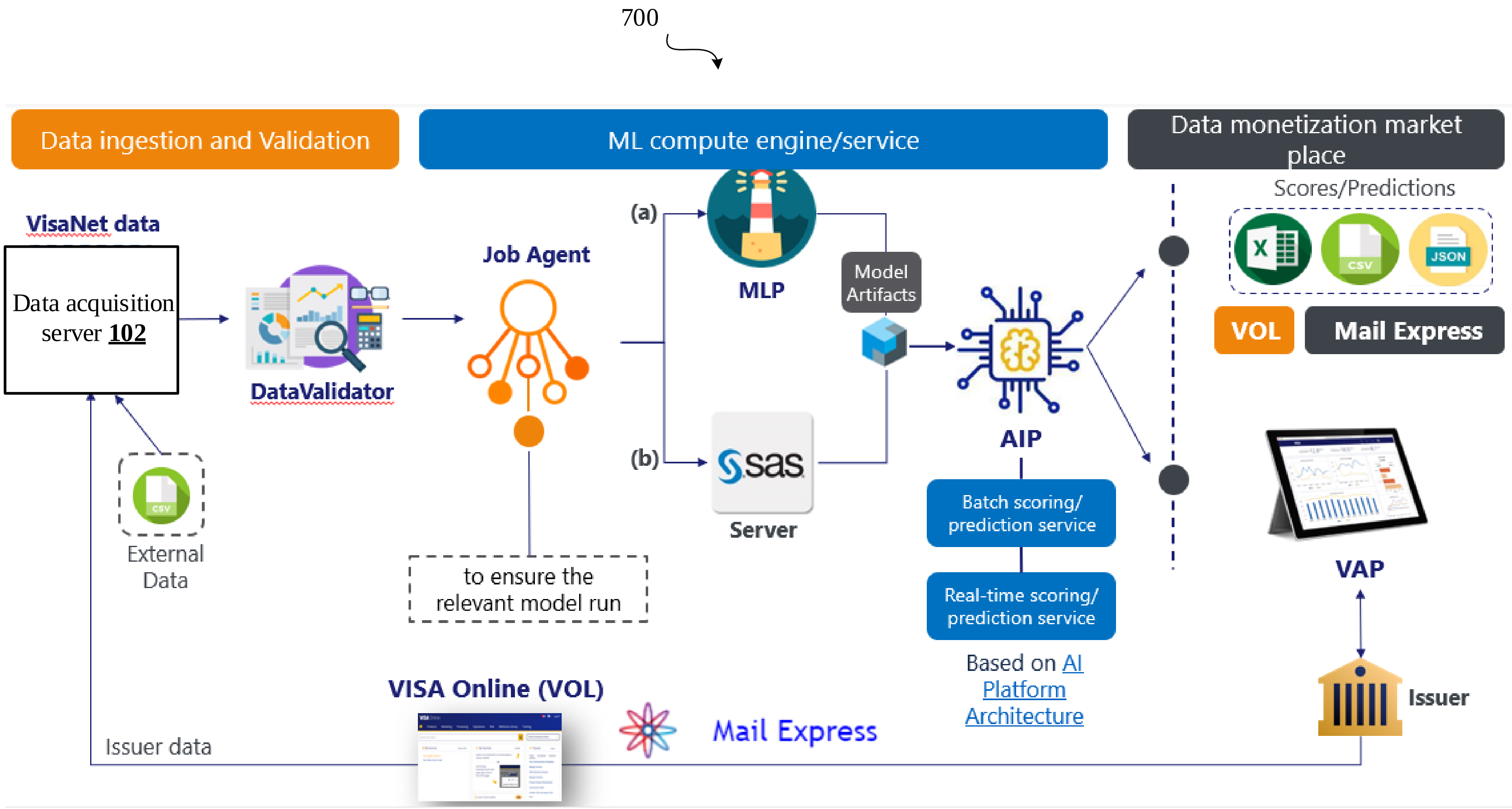
700
Data ingestion and Validation
ML compute engine/service
Data monetization market place
Scores/Predictions
VisaNet data
Data acquisition server 102
DataValidator
Job Agent
(a)
MLP
Model Artifacts
(b)
sas
Server
AIP
VOL
Mail Express
External Data
to ensure the relevant model run
Batch scoring/ prediction service
Real-time scoring/ prediction service
Based on AI Platform Architecture
VAP
Issuer
VISA Online (VOL)
Mail Express
Issuer data

FIGURE 7

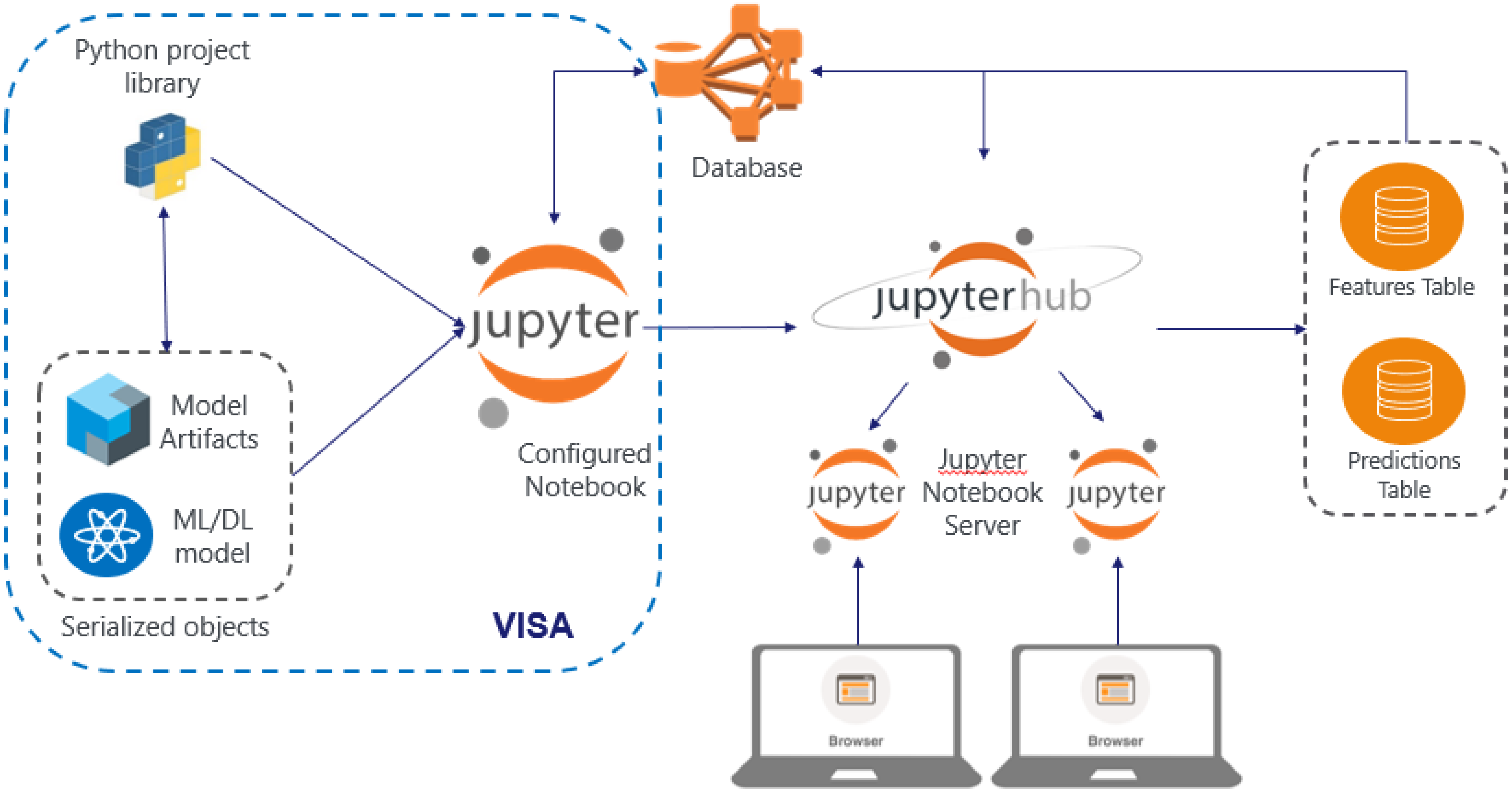
Python project library
Database
Model Artifacts
ML/DL model
Serialized objects
jupyter
Configured Notebook
VISA
jupyterhub
jupyter
Jupyter Notebook Server
jupyter
Features Table
Predictions Table
Browser
Browser

FIGURE 8

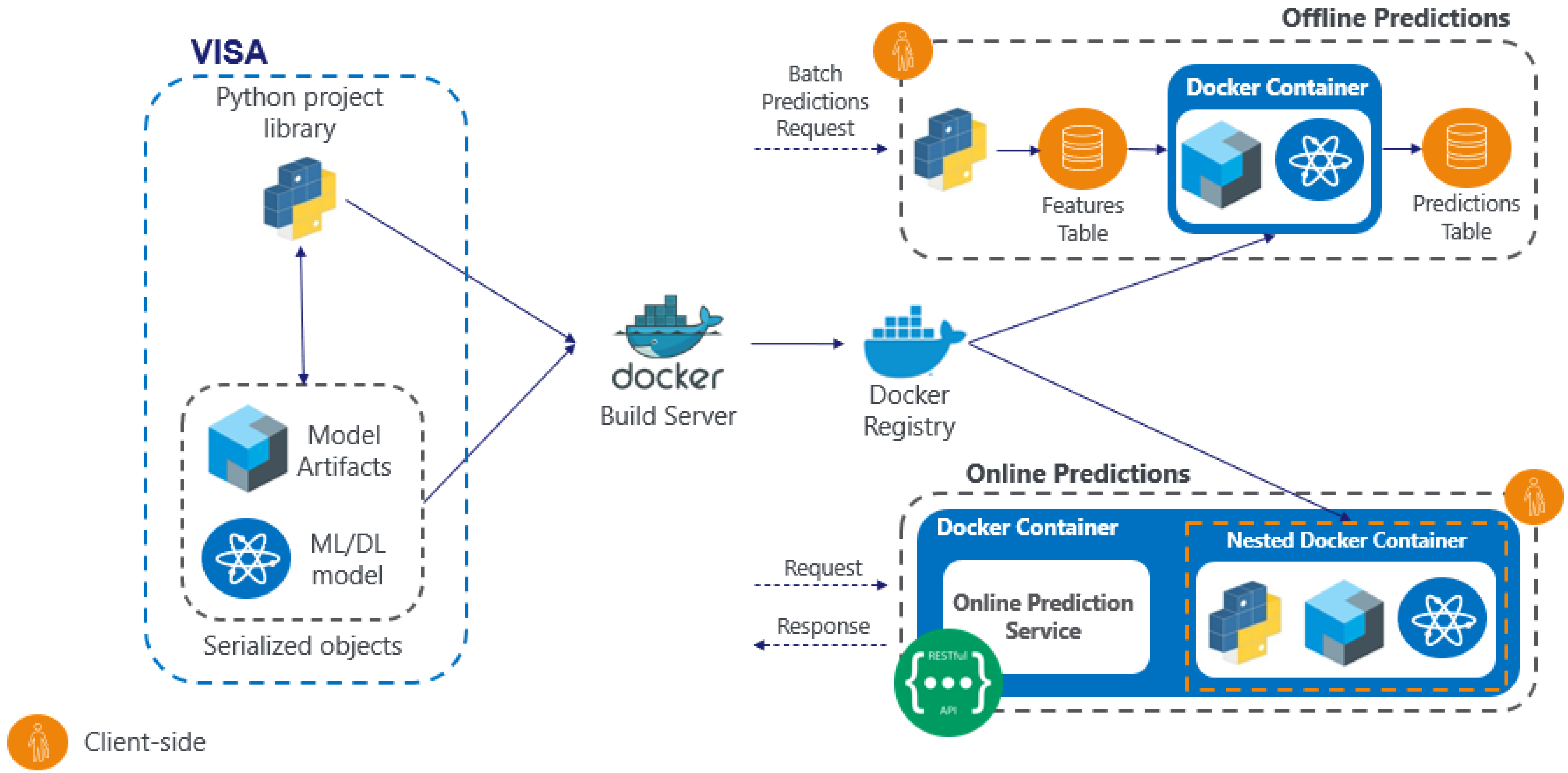
VISA
Python project library
Model Artifacts
ML/DL model
Serialized objects
Client-side
docker
Build Server
Docker Registry
Offline Predictions
Batch Predictions Request
Features Table
Docker Container
Predictions Table
Online Predictions
Request
Response
Docker Container
Online Prediction Service
Nested Docker Container
RESTful
API

FIGURE 9

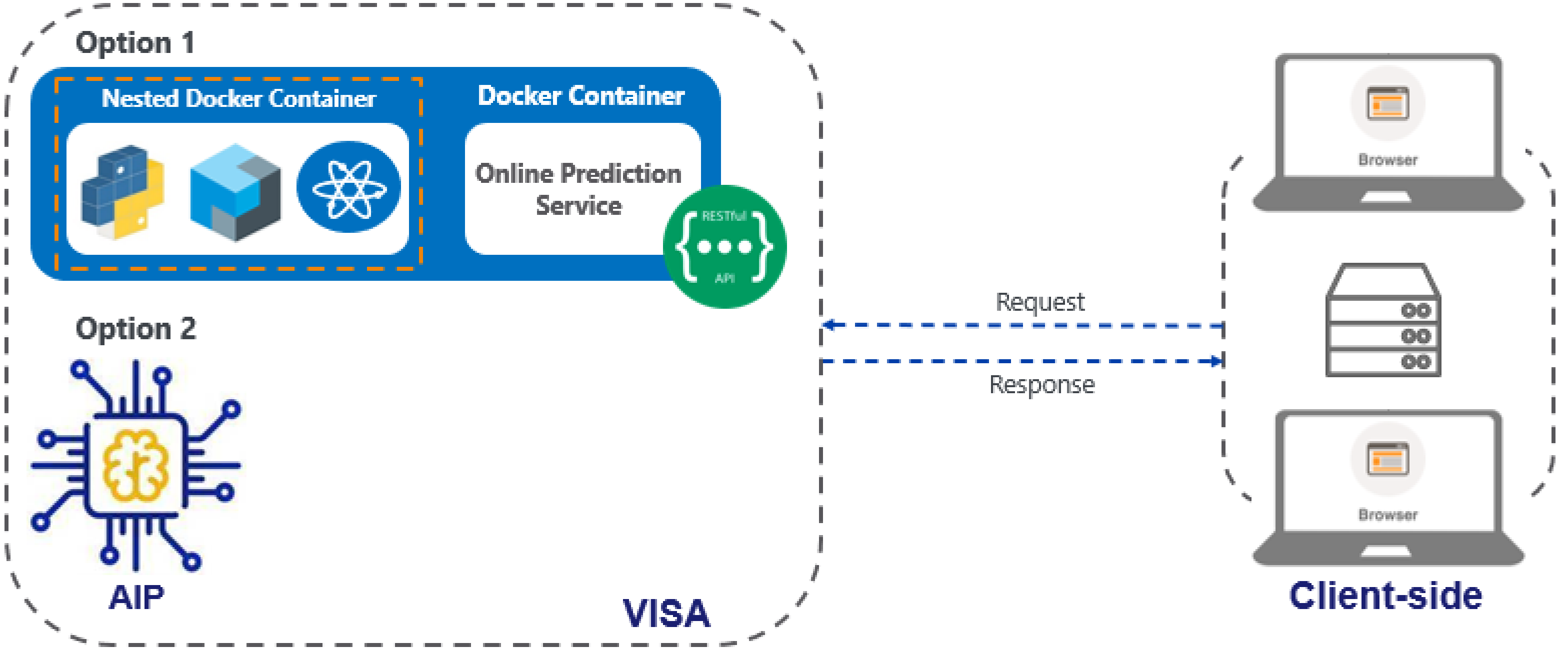
Option 1
Nested Docker Container
Docker Container
Online Prediction Service
RESTful
API
Option 2
AIP
VISA
Request
Response
Browser
Browser
Client-side

FIGURE 10

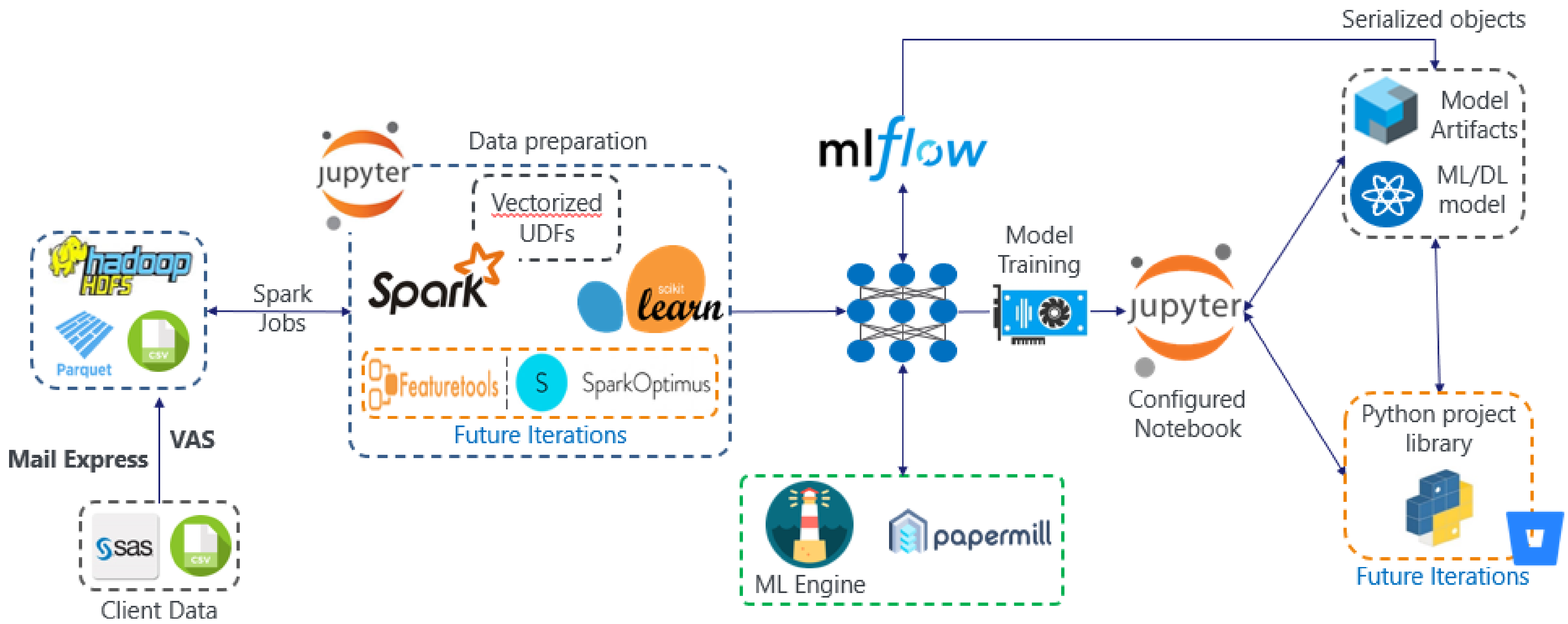
Serialized objects
Model Artifacts
ML/DL model
mlflow
Data preparation
jupyter
Vectorized UDFs
Spark
scikit learn
Spark Jobs
hadoop HDFS
Parquet
CSV
Featuretools
SparkOptimus
Future Iterations
Model Training
jupyter
Configured Notebook
Python project library
Future Iterations
Mail Express
VAS
sas
CSV
Client Data
ML Engine
papermill

FIGURE 11

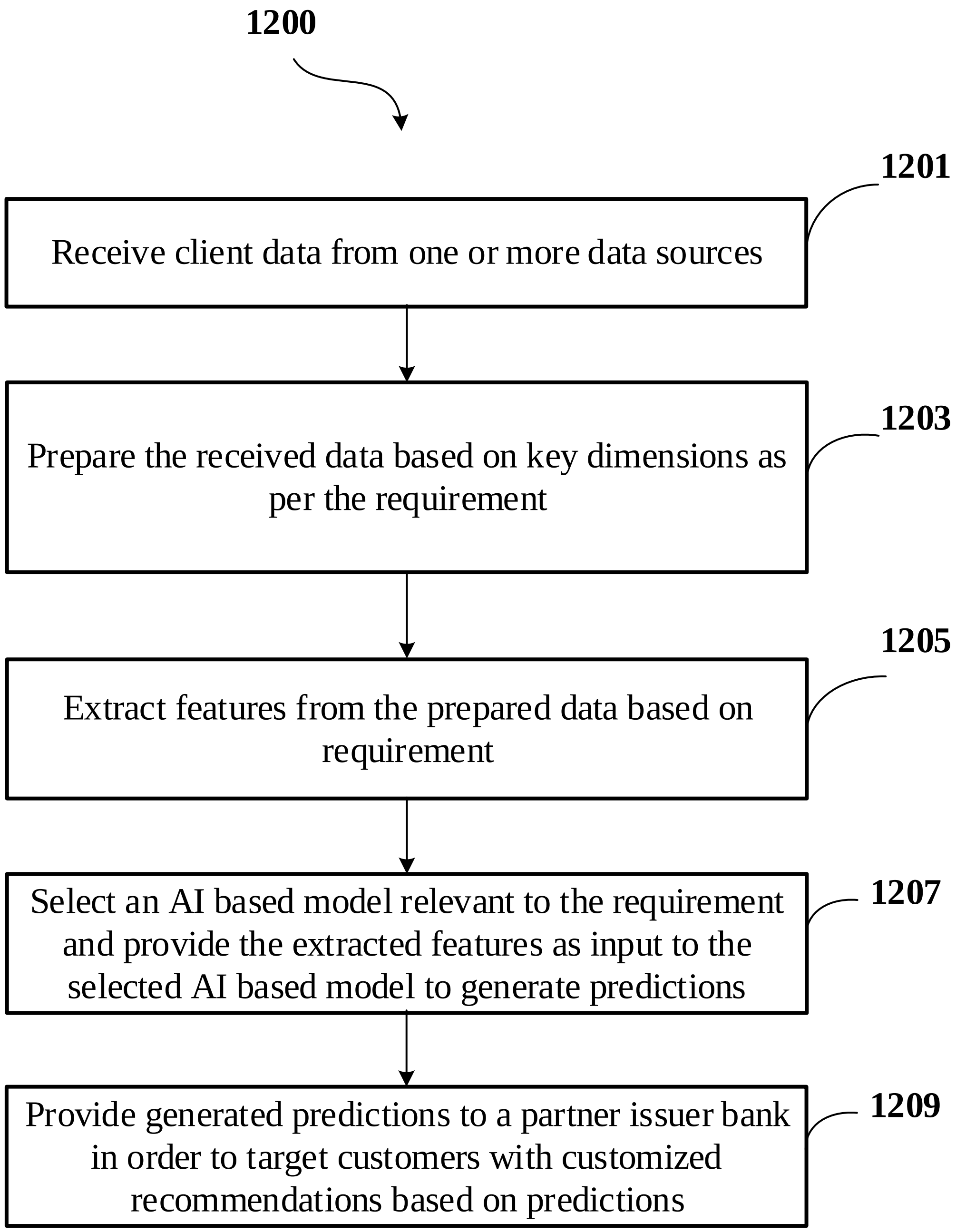
1200
1201
Receive client data from one or more data sources
1203
Prepare the received data based on key dimensions as per the requirement
1205
Extract features from the prepared data based on requirement
1207
Select an AI based model relevant to the requirement and provide the extracted features as input to the selected AI based model to generate predictions
1209
Provide generated predictions to a partner issuer bank in order to target customers with customized recommendations based on predictions

FIGURE 12

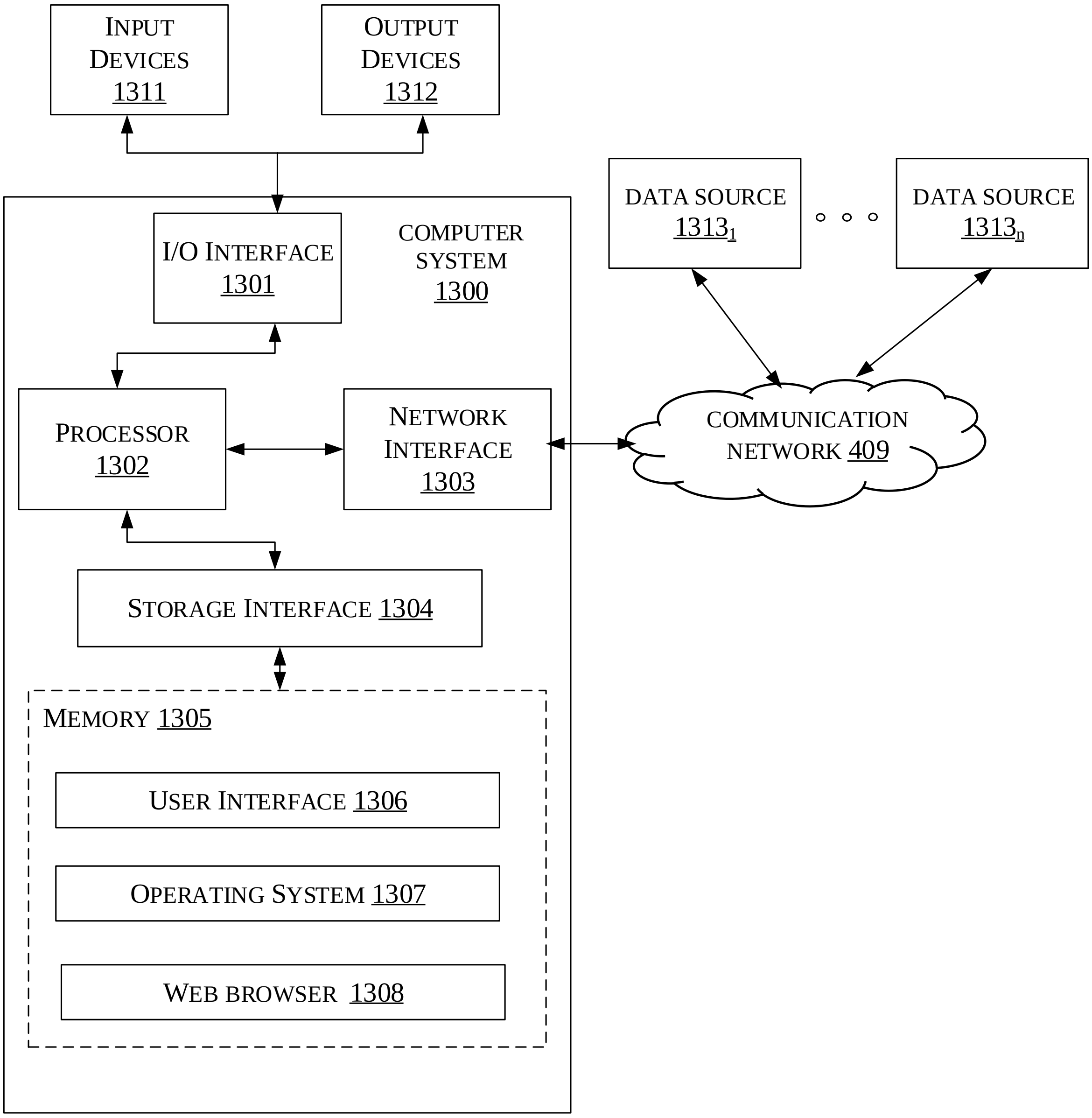
INPUT DEVICES 1311
OUTPUT DEVICES 1312
I/O INTERFACE 1301
COMPUTER SYSTEM 1300
DATA SOURCE 1313_1
DATA SOURCE 1313_n
PROCESSOR 1302
NETWORK INTERFACE 1303
COMMUNICATION NETWORK 409
STORAGE INTERFACE 1304
MEMORY 1305
USER INTERFACE 1306
OPERATING SYSTEM 1307
WEB BROWSER 1308

FIGURE 13