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W27310

# ALLIANZ: PREDICTING DIRECT DEBIT WITH MACHINE LEARNING

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It was January 2021, and Sudaman Thoppan Mohanchandralal, chief data and analytics officer (CDAO) of Allianz Benelux SA (Allianz), was reflecting on a recent company board meeting. He had had a discussion with Allianz's regional chief executive officer, Anthony Bradshaw, and chief underwriter officer, Eric van den Heuvel, debating the low number of customers that used direct debit and how the premiums were collected. Increasing the use of direct debit was especially interesting to Allianz, as it could be used as an instrument to create a more reliable cash flow. In the fast-paced environment of the insurance sector, this was vital to ensure cash was available for future opportunities.

As Allianz's CDAO, it was Mohanchandralal's job to investigate, with his team, how the company could leverage customer data to create value. Excited to tackle this new project, Mohanchandralal and his data office team first had to fully understand the business problem and collect internal data on contracts, brokers, and customers. This would provide an overview of who Allianz's customers were, who had sold the customers their contracts, and how the premiums were collected. From there, the goal was to find interesting patterns in the data and to build predictive models. Based on the results of these analyses, the data office team could provide insights to management that would help to increase the use of direct debit.

## ABOUT ALLIANZ

Allianz Group, a multinational financial services group, was founded in 1890 in Berlin, Germany. In 2021, Allianz provided life and health insurance, non-life insurance, and asset management products and services to more than eighty-eight million customers in over seventy countries, making it the world's third-largest financial services provider (see Exhibit 1).

Allianz always strove to embrace the power of innovation and the added value of digitalization. It established the data office in Belgium as the main hub of Allianz. The data office consisted of more than forty data experts and was directed by Mohanchandralal. As CDAO, Mohanchandralal was responsible for transforming Allianz into a more data-driven company. Mohanchandralal had been working at Allianz for four years, and he reported directly to Bradshaw, Allianz's regional chief executive officer.[1]

[1] Bradshaw was replaced by Joos Louwerier as regional chief executive officer of Allianz in July 2021.

Mohanchandralal and his data office team worked in close collaboration with Allianz's different business departments. Using business intelligence and machine learning, they tried to improve pricing, detect and prevent fraud, simplify operations, handle claims, and enhance customer and broker centricity. To structure a data science project, the Allianz data office team used the cross-industry standard for data mining (CRISP-DM) framework. This framework allowed the team to split up the data science process into six distinct phases. A large poster of this framework could be found on the wall of the data office department (see Exhibit 2).

## UNDERSTANDING THE BUSINESS PROBLEM

The first phase was to acquire a clear understanding of the objectives and requirements of the project and to develop a deep understanding of the business problem itself. In this project, Mohanchandralal wanted himself and his team to be aware of a few things: how direct debit worked exactly, what the advantages of direct debit were for Allianz's clients, and what the advantages of direct debit were for Allianz. These elements were necessary for knowing which analyses to conduct and for developing an appropriate strategy.

### Direct Debit

To learn more about the use of direct debit, Mohanchandralal turned to his colleagues in the finance department. First, his finance colleagues explained that direct debit allowed for outstanding invoices to be collected from a debtor directly. They then pointed out that there was a difference between setting up the payment construction for business-to-consumer customers and for business-to-business (B2B) customers. As both consumers and businesses would likely be present in the dataset that Mohanchandralal would be working on, he was interested in both.

His finance colleagues explained how direct debit worked for countries within the single euro payments area, where no distinction was made between domestic and European transactions. Direct debit allowed creditors to directly collect outstanding invoices from the debtor.

Setting up this payment construction consisted of several steps (see Exhibit 3). First, the creditor sent a mandate to the debtor. The debtor permitted the creditor to debit the debtor's account by signing this contract. Nevertheless, before a creditor could debit the debtor's account, the creditor would have to send the debtor a pre-notification outlining the details of the contract at least fourteen days in advance. After the creditor's and the debtor's banks shared all necessary information, the agreed amount would be debited from the debtor's account, while the creditor's account would be credited with the same amount.

The finance team did point out that even with direct debit, the creditor still faced some potential risks. Before or after the settlement date, it was possible to receive a notification that the transaction could not be processed in the normal way. This could be due to multiple reasons, such as a reversal, a request for cancellation, or a revocation (on the creditor's side). However, other possible reasons for such a notification were if the debtor's account did not contain sufficient funds or if the debtor asked for a refusal or a refund.

In the B2B case, there were some differences. The main difference was that under the B2B mandate, the debtor was not entitled to a refund. Further, the debtor also needed to have authorized the B2B direct debit to the debtor's bank, and there was a smaller time span for other actions, such as a return or a reversal. The B2B scheme was optional, and not all banks supported it. Both the creditor's and debtor's banks needed to be flagged as B2B enabled.

### Advantages for Allianz's Clients

Mohanchandralal thanked the finance team for this information on the technical workings of direct debit. To come up with a good strategy, he also wanted to know how direct debit could benefit Allianz's clients. The finance team mentioned three clear customer advantages: First, direct debit was very straightforward for clients to set up; they would not need to change the payment details unless they changed banks. Once direct debit was set up, customers never had to think about it again, and this offered a high level of convenience. Second, since the payments happened automatically and on time, no late fees would ever be charged. Third, direct debit made budgeting and planning easier for the clients, as they knew exactly how much would be withdrawn from their accounts and when.

### Advantages for Allianz

Mohanchandralal wanted to fully understand the exact objective of the project and why direct debit fit well with Allianz's strategy. Bradshaw and Van den Heuvel emphasized that this payment method would help with managing Allianz's working capital.

The insurance industry was a fast-paced environment, and it was crucial to have enough money on hand to invest in new opportunities. Using the cash conversion cycle (CCC), Allianz monitored how long it took before its services were converted into cash (see Exhibit 4). This was seen as a crucial metric for working capital management, as it incorporated both the receivables conversion period and the payables deferral period. A short cycle meant that the business was operating efficiently and that a steady income was generated. This allowed for cash to be freed up and invested in other projects. Direct debit fit well within this framework, as it positively influenced the accounts receivable collection period. Hence, this payment method reduced the time that cash was tied up as working capital and thus shortened the CCC.

Besides the shortened CCC, other advantages also made this project valuable for Allianz. Direct debit created a more reliable cash flow, as Allianz knew precisely when and how much money came in. This allowed for better forecasting and planning. Another advantage was the reduction in cost and complexity of the administrative process. A lot of the manual effort that went into making the invoices and collecting the payments would be reduced. Another advantage for Allianz was the increase in trust and commitment from its customers. Finally, the payments continued unless the customer or business explicitly requested a change, which meant churn rates would decrease.

Despite these apparent advantages, few customers used this payment option. On average, direct debit was used in 65 per cent of all insurance contracts, but for Allianz, only 21 per cent of its insurance contracts were paid via direct debit. Therefore, the company wanted to increase this rate to approximate the average. However, Allianz did not want a costly campaign that targeted all of its customers. The goal of the project was to come up with an intelligent way to identify the most interesting customers and then to focus efforts on them.

## DATA COLLECTION

Now that Mohanchandralal and his team had gathered enough information to understand the problem, they moved on to the second step in the CRISP-DM model: collecting the data. For this project, they used data from their property and casualty claims in Belgium (see *Allianz: Predicting Direct Debit with Machine Learning – Student Spreadsheet,* Ivey product no. W31816). This dataset provided information on three levels (broker, customer, and product) and the variable of interest—that is, whether the contract used direct debit. The data was at the contract level, so each instance represented one contract. To ensure that everybody in the team knew what every variable meant, a data dictionary was constructed (see Exhibit 5). To visualize the dataset's structure and how the three levels were related, someone on the team also constructed an entity diagram (see Exhibit 6). In the entity diagram, the relations between the levels were indicated with numbers. For example, each contract was linked to one customer ("1"), but a customer could have one or more contracts ("1 .. *"). Further, each customer could have multiple brokers, and a broker could have multiple clients.

As some of the members were new to the team, a more senior member reminded them of certain Allianz policies: Allianz obliged its customers to use direct debit for the monthly payment contracts. Customers consisted of both people and enterprises, and an enterprise had the value "No age" as its age in the dataset.

Because all the data came from Belgian contracts, the local context was also mentioned again, as it could be important to derive insightful conclusions. Belgium was split into three regions: Flanders, Wallonia, and Brussels. Each region was then divided into provinces (see Exhibit 7). The dataset provided the region and province for both the broker and the customer.

## STRATEGY FOR ANALYSIS

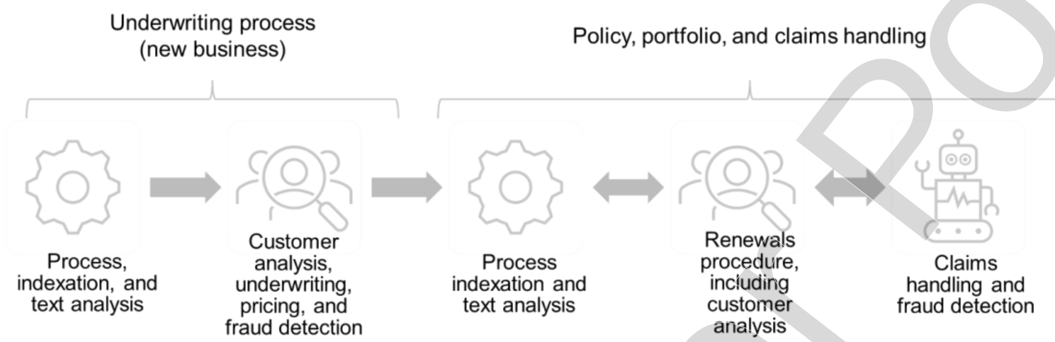
After reviewing the information on the importance and use of direct debit as well as the dataset they had gathered, Mohanchandralal and his team developed a strategy for how they wanted to tackle the problem. One of them mentioned that "the most important step in any data science project is to develop a deep understanding and appreciation for the data at hand." The others quickly agreed, so they decided that they wanted to do a data exploration as a first step. It was important that any potential problems with the data were dealt with so that the rest of the analysis happened with clean data. At the end of the exploration stage, everybody needed to have a clear view of who the customers and the brokers were, and to have developed an intuition about how the characteristics associated with the brokers and customers were related to the use of direct debit.

Building on this, one data office team member mentioned that the analysis could be extended by adding a clustering model. He argued that some interesting customer segments could be identified this way. Later on, these segments might be used by the marketing department for personalized marketing actions.

"So now," Mohanchandralal said, "we know who our customers and brokers are and have grouped similar customers into segments. However, what I'm really interested in is what drives some customers to use direct debit while others do not." Therefore, the last type of analysis he wanted to conduct was predictive modelling to predict who would use direct debit. Accordingly, the model could help identify the customers most likely to accept direct debit. Afterward, some interpretation techniques could be applied to the model by looking at which features were most relevant in predicting the use of direct debit. This could provide real business insights that Mohanchandralal's colleagues could then use.

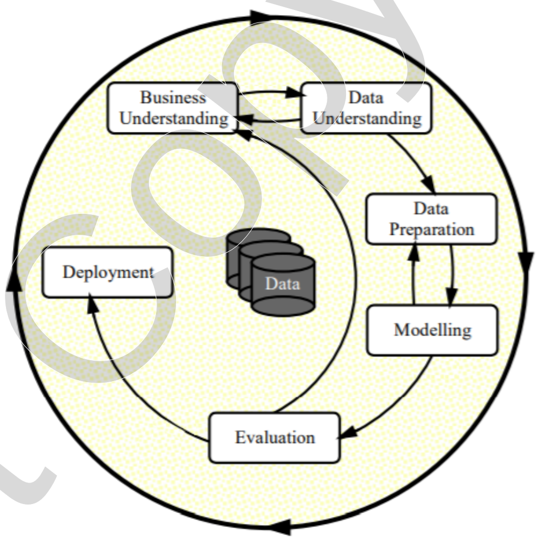
Mohanchandralal concluded the meeting by reminding everybody that they should not forget that the goal of the project was to develop a data-driven strategy to increase the use of direct debit, which would be presented to the board.

## EXHIBIT 1: THE INSURANCE PROCESS



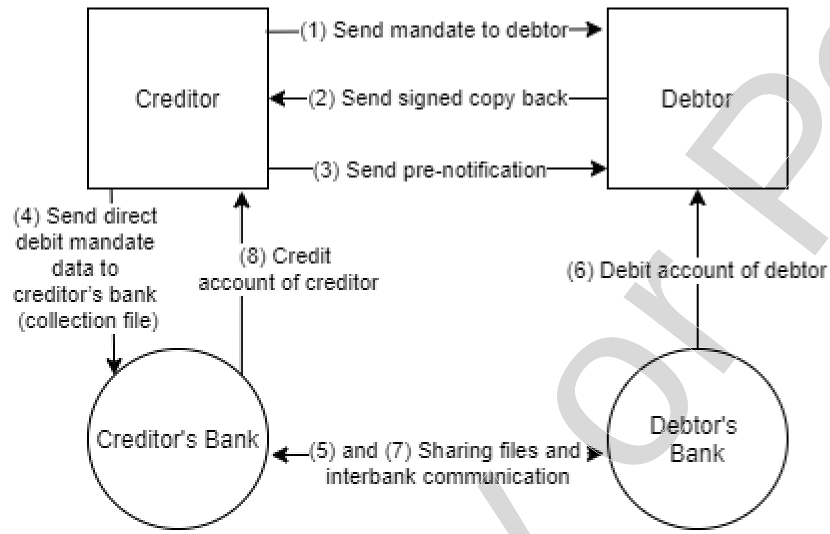

Source: Created by the authors, adapted from company documents.

## EXHIBIT 2: CROSS-INDUSTRY STANDARD FOR DATA MINING MODEL



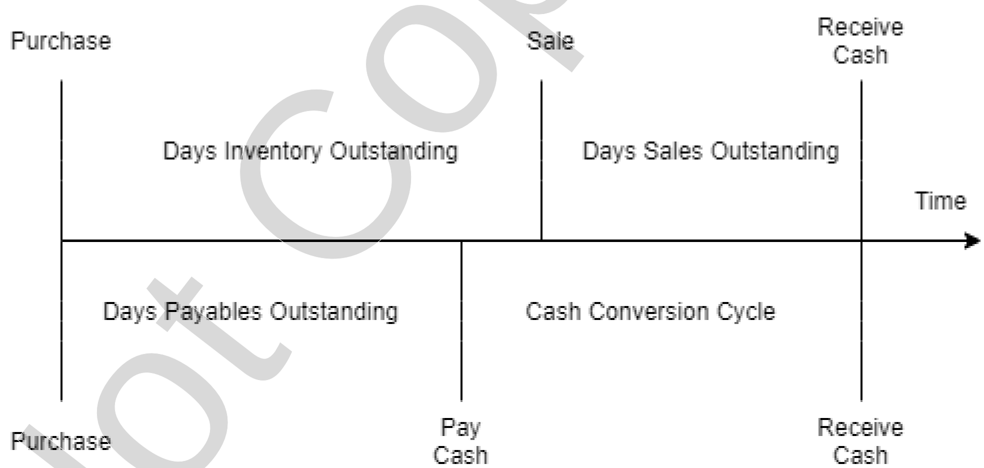

Source: Rüdiger Wirth and Jochen Hipp, "CRISP-DM: Towards a Standard Process Model for Data Mining," in *Practical Application of Knowledge Discovery and Data Mining* (Lancashire, UK: Practical Application Company, 2000), 29–40, http://cs.unibo.it/~danilo.montesi/CBD/Beatriz/10.1.1.198.5133.pdf.

### EXHIBIT 3: SINGLE EURO PAYMENTS AREA DIRECT DEBIT




Source: Created by the authors, based on company files.

### EXHIBIT 4: THE CASH CONVERSION CYCLE



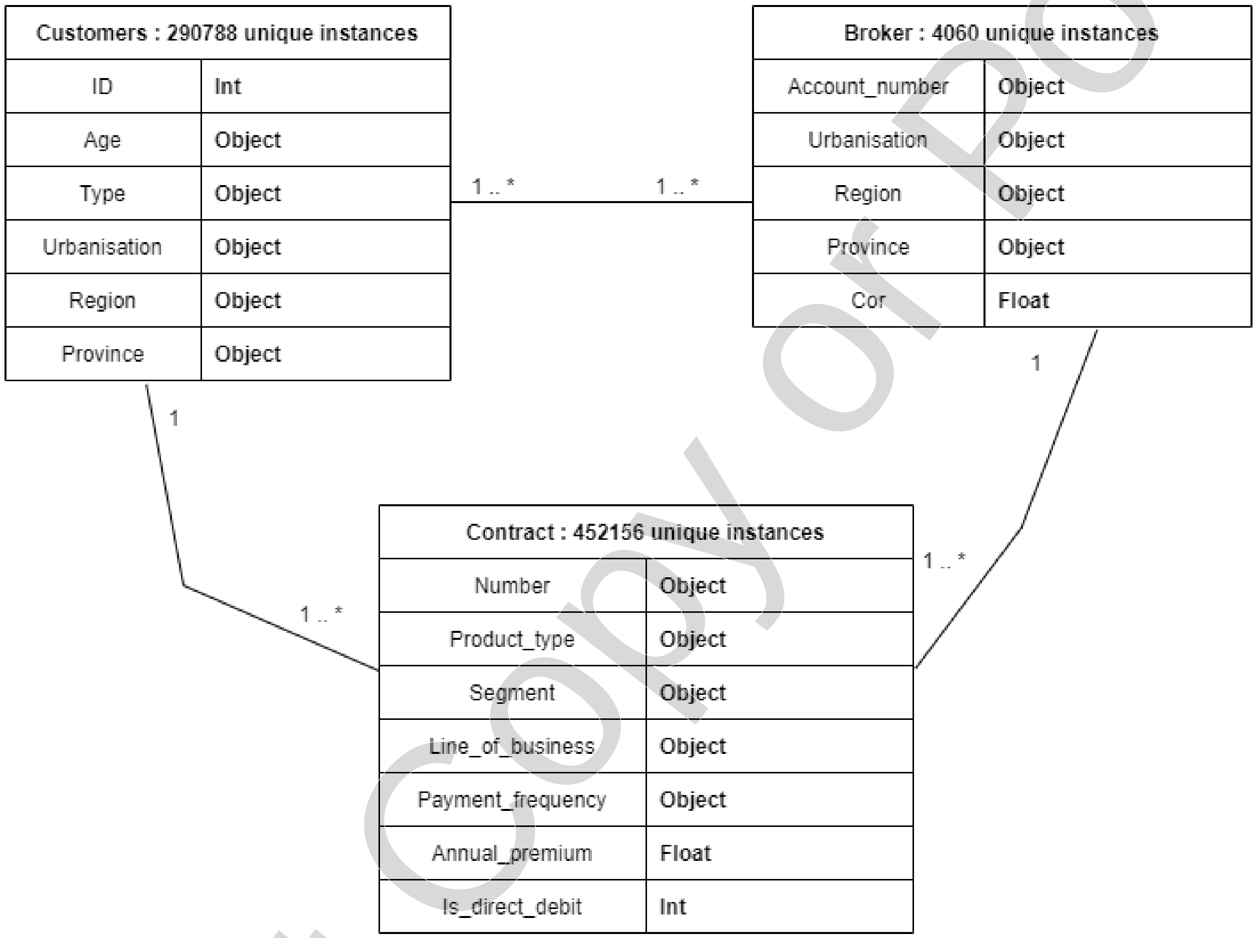

Source: Created by the authors based on Verlyn D. Richards and Eugene J. Laughlin, "A Cash Conversion Cycle Approach to Liquidity Analysis," *Financial Management* 9, no. 1 (Spring 1980): 32–38, https://doi.org/10.2307/3665310.

## EXHIBIT 5: DATA DICTIONARY

| Field name | Data type | Description |
|---|---|---|
| **Broker_account_number** | Object | Broker identifier |
| **Contract_number** | Object | Contract identifier |
| **Customer_segment** | Object | Segment of the contract; possible values include “Retail,” “SME,” and “Midcorp” |
| **Line_of_business** | Object | Information on which line of business the contract belongs to; possible values include “A - Motor,” “D - Property,” “E - Liability,” “I - Property,” “N - Accident,” “P - Liability,” and “R - Engineering” |
| **Product_type** | Object | Product-specific information |
| **Annual_premium** | Float | Annual premium charged for the contract |
| **Payment_frequency** | Object | Payment frequency of premiums for the contract |
| **Customer_ID** | Int | Customer identifier |
| **Customer_age** | Object | Age of the customer, categorized into the following buckets: “A = 18-24,” “B = 25-29,” “C = 30-39,” “D = 40-69,” and “S = +69”; the age for an “Enterprise” has been given the value “No age” |
| **Customer_type** | Object | Information on the type of customer (i.e., “Physical person” or “Enterprise”); an SME can also be a “Physical person” (for self-employed companies) |
| **Customer_urbanization** | Object | The urbanization zone to which the broker belongs (“Urban” or “Rural”) |
| **Customer_region** | Object | The region that the customer belongs to in Belgium |
| **Customer_province** | Object | The province that the customer belongs to in Belgium |
| **Broker_urbanization** | Object | The urbanization zone to which the broker belongs (“Urban” or “Rural”) |
| **Broker_region** | Object | The region that the broker belongs to in Belgium |
| **Broker_province** | Object | The province that the broker belongs to in Belgium |
| **Is_direct_debit** | Int | Flag to indicate whether the contract has direct-debit payment of premium: “0” = not direct debit, “1” = direct debit |
| **Broker_cor** | Float | The combined ratio of the broker: <100 indicates that the broker is profitable; >100 indicates that the broker is not profitable (the broker is more profitable if the value is lower) |

Note: Object = categorical value; Int = integer number; Float = decimal number; SME = small and medium-sized enterprise; Midcorp = Mid-market companies, larger than SMEs.
Source: Company files.

## EXHIBIT 6: ENTITY DIAGRAM




Note: Each contract was linked to one customer (“1”), but a customer could have one or more contracts (“1 .. *”).
Source: Created by the authors.

## EXHIBIT 7: PROVINCES AND REGIONS IN BELGIUM

**Provinces**

| **Name** | **Data value** |
|---|---|
| West-Vlaanderen | VWV |
| Oost-Vlaanderen | VOV |
| Antwerpen | VAN |
| Vlaams-Brabant | VBR |
| Limburg | VLI |
| Brussels | BRU |
| Hainaut | WHT |
| Brabant Wallon | WBR |
| Namur | WNA |
| Liège | WLG |
| Luxembourg | WLX |


**Regions**

| **Name** | **Data value** |
|---|---|
| Flanders | FLA |
| Brussels | BRU |
| Wallonia | WAL |


Source: Created by the authors using the Python package GeoPandas.