

THE EVOLUTION OF DEBT PORTFOLIO SEGMENTATION

HOW AN ANALYTICS-ENABLED
STRATEGY CAN ELEVATE DEBT
MANAGEMENT



TABLE OF CONTENTS

Why Read This Paper	3
Introduction	4
Operational Segmentation Criteria	5
Practical Examples Of Analytics Use	7
Confronting A Key Challenge	8
How QUALCO D3E Can Help	8



WHY READ THIS PAPER

Segmentation of debt portfolios appears as one of the most effective ways to improve customer engagement significantly. In combination with unexpected external events, the evolving customer behaviour puts the onus on the financial organisations' functions to better target their customers and offer highly personalised experiences.

Customer segmentation can offer creditors different treatments according to different needs and circumstances. However, effective segmentation can be laborious when applied in practice due to the siloed information across several platforms and systems that creditors have at their disposal. With advanced Analytics and Machine-Learning algorithms, businesses managing debt can obtain a granular picture of their at-risk customers. This detailed information can classify customers into segments and design more efficient and effective contact strategies.

Through our exclusive report, we shed light on the following:

- How can creditors achieve highly targeted segmentation in practice
- Segmentation criteria and approaches to enhance collections performance
- How collection analytics blends in with modern technology
- Practical examples used in the segmentation process for recovering NPLs



INTRODUCTION

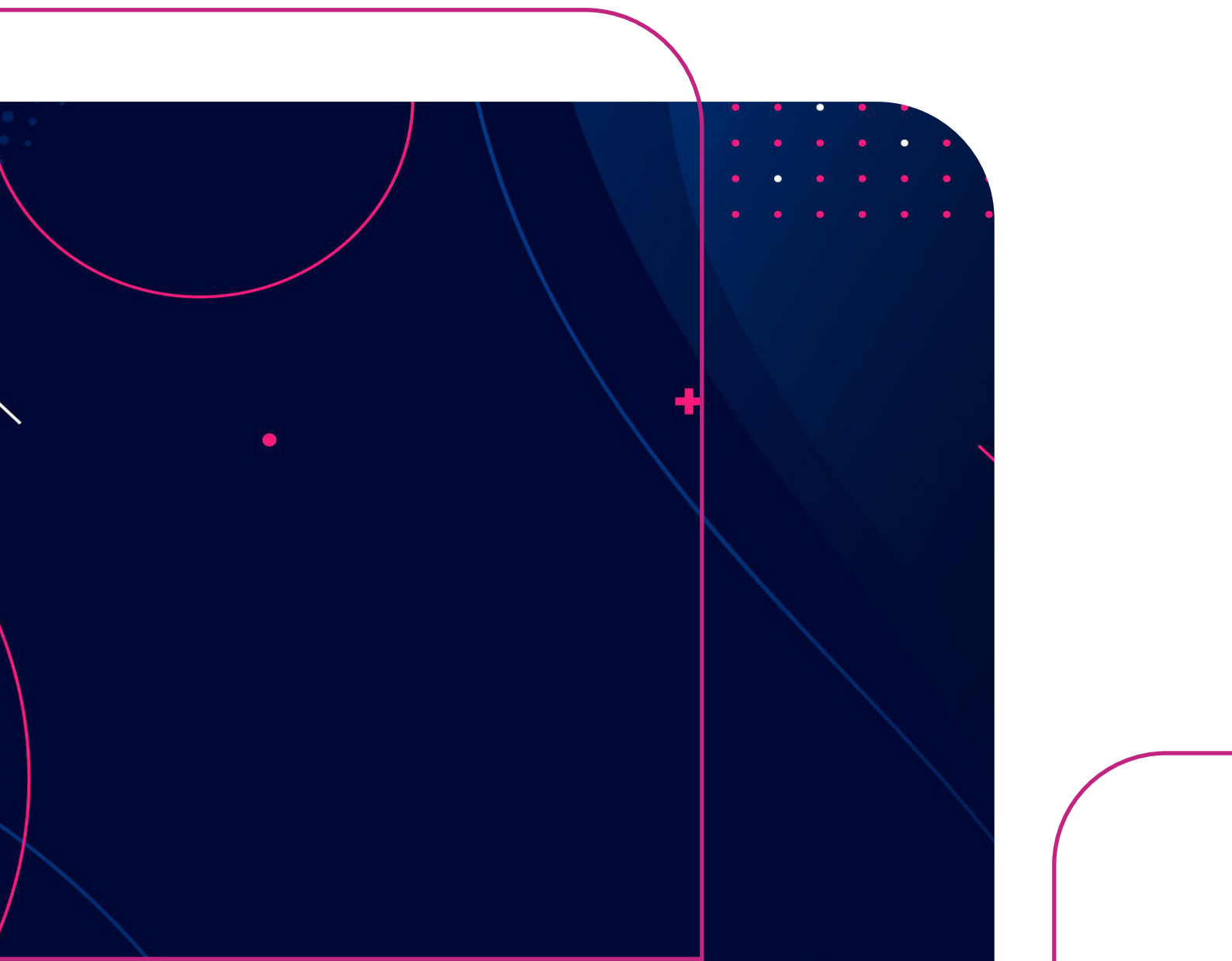
Organisations managing debt, especially banks, traditionally segment the customers and the cases they manage using mostly segments defined by regulatory reporting criteria. Typically, cases are segmented according to credit type (business loans, mortgages, consumer loans etc.) and the days past due, often expressed in buckets.

Regulatory requirements mandate that as arrears increase month after month and a case move through buckets, creditors must reduce their expectations for recovering the total amount due. They should also include accordingly provisions on their balance sheets.

Regulatory reporting segments are suitable for defining business targets (for example, reducing NPL in buckets 7-12 by a target percentage within a specific period) but provide only a high-level segmentation, of limited use in defining an efficient customer approach and selecting the most appropriate treatment per case.

Operational criteria segmentation is usually an effort to reconcile credit risk targets and regulatory reporting obligations with practical considerations and the reality of day-to-day collections operations.

Segmentation can become a lot more effective through analytics and data.



OPERATIONAL SEGMENTATION CRITERIA

Bucket history is obviously important, and patterns such as being in the same bucket for long periods can and should be detected. For example, some debtors admit being advised that they will not have any significant consequences (except for late fees and deterioration of their credit history) by constantly remaining on bucket 3.

This practice bears consequences for banks as these early arrears must be reported as Non Performing Loans (NPL), affect impairment, and set a bad example for other customers.

Whether a loan is secured or not is another typical segmentation criterion. And among secured loans, the Loan to Value (LTV) ratio is a meaningful segmentation criterion, as loans with an LTV greater than 100 are not adequately secured.

Operational criteria can go beyond buckets or the distinction between secured and unsecured loans. Not all secured mortgages on bucket 5, for example, are the same:

Behind each customer's delinquency can be different causes and intentions.

The more sophisticated creditors enrich their segmentation criteria with empirical and behavioural observations. This does not happen to override or second-guess analytics but rather as an injection of domain knowledge that may not be apparent in the data so far.

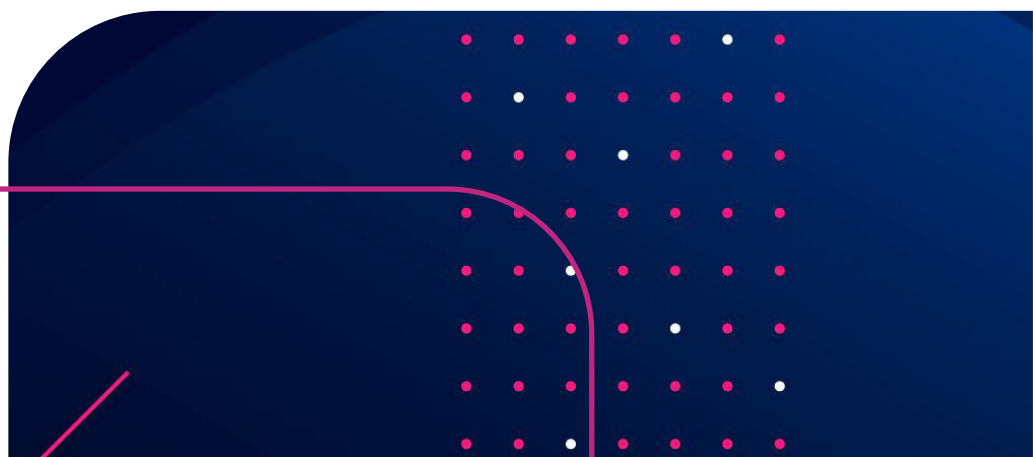
Customer information, such as profession and sources of income, can be used to better segment and act proactively on segments likely to move into NPL.

When the first wave of COVID-19 restrictions hit all economies in early 2020, some creditors decided to approach first the categories of customers rendered vulnerable (i.e. workers on furlough, or employed in the transportation or tourism sector), and propose solutions to prevent the creation of new NPL rather than wait for loans to move into arrears. As knowledge that these industries would be affected was readily available, it made no sense to wait for the actual impact to be reflected in incoming data. This proactive approach also improves the overall customer experience.

Past customer requests for moratoria or lower installments, the respect or non-respect of past payment plans, and any past demands by the customer (regardless of whether they have been approved or not) can all be taken into consideration to better segment portfolios.

Customer behaviour, such as the willingness to communicate with creditors and seek a mutually beneficial solution or the tendency toward confrontation and litigation, can also be used for operational segmentation.

Besides the obvious business benefits, borrowers appreciate such a proactive approach as they see that a creditor is responsive to events that affect their lives.



Modern analytics tools:

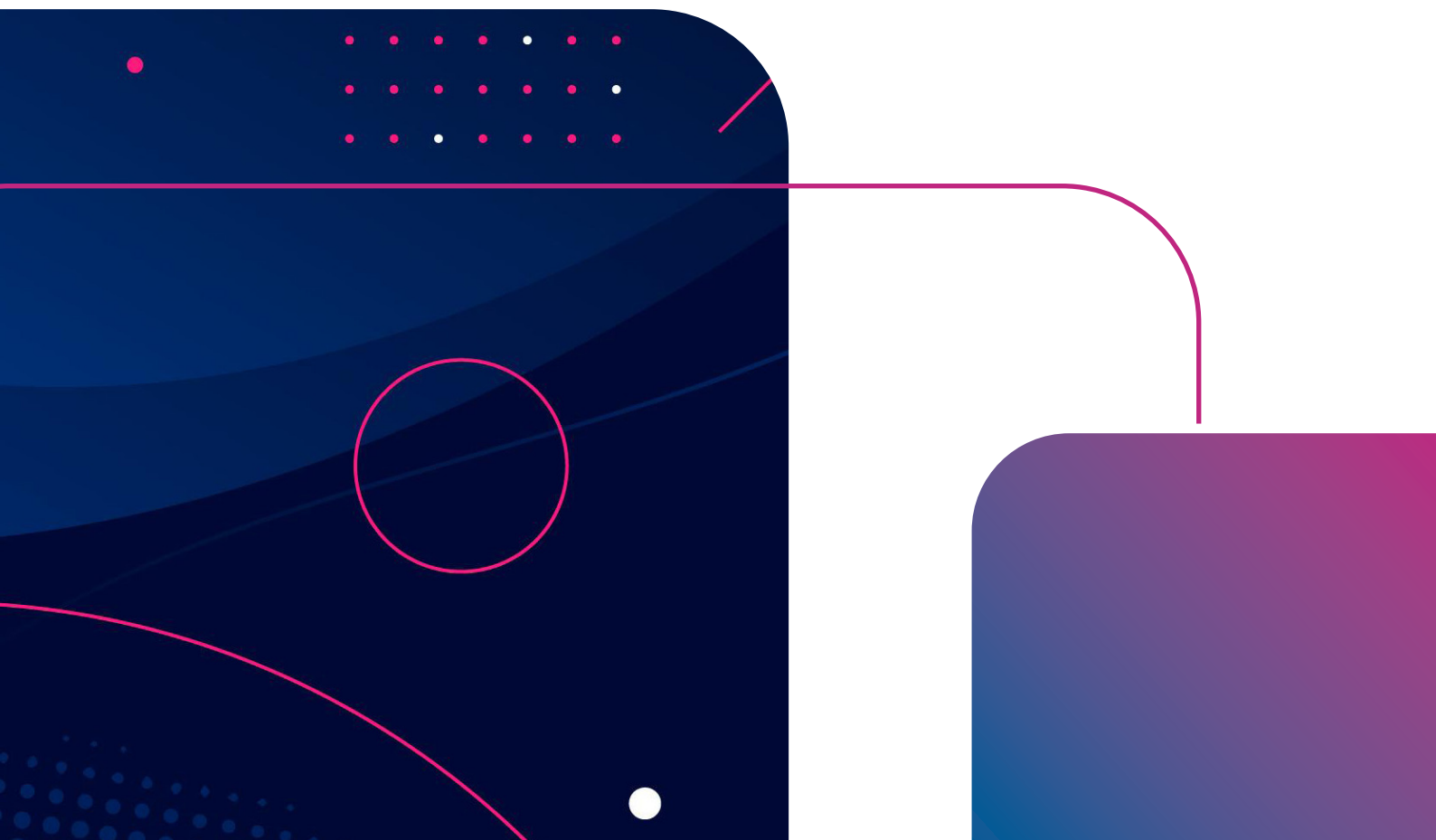
- › Allow segmentation to become more efficient and much more targeted.
- › Can split up portfolios into homogeneous segments concerning the borrower's response to specific treatments.
- › Enable a proactive approach, as the creditor can match the available treatments for different types of delinquency with the customer segments they are best suited for.
- › Make inconsistencies easier to recognise and enable process standardisation.
- › Eliminate bias that can sometimes be present when segmentation is based on empirical criteria.

In NPL management, the viability of the solutions proposed to customers is crucial. Analytics can help predict the viability and prevent offering payment plans and debt restructuring that will not be respected by customers and will be back in the NPL perimeter soon.

In early collections, predictive analytics can help a creditor identify the cases that are more likely to be in arrears “accidentally” and distinguish them from those that are more likely to reach the “late” or “legal” stages and adjust the approach to those customers accordingly.

Adopting the right tone in communications, suggesting the appropriate solutions where needed, or becoming more alert on cases where there are serious indications that debtors are not acting in good faith and are trying to gain time to organise their insolvency.

Also, analytics can help predict whether a debt is collectable or the optimal way to contact each debtor, the best times to call, or what other means of communication might be more effective (e-mail, SMS). Therefore, new operational segments and contact queues emerge, such as “Willing to talk to an agent”, “responds to written communication”, etc.



PRACTICAL EXAMPLES OF ANALYTICS USE



A great example of applying analytics in NPL segmentation is predicting the outcome of pending litigation by analysing statistical data of past court decisions and identifying common characteristics among cases. This can save legal costs and provisions over time.

For instance, this can be implemented on **Greece's** huge volumes of “over-indebtedness” applications filed under law 3869/10 and its amendments. This law has caused essential parts of the banks’ portfolios to remain “unmanageable” for several years, pending court hearings and decisions.

For years, banks and their legal counselors have been able to empirically predict the most likely outcome for the cases of customers seeking Law 3869 protection.

With the use of analytics, and as the volume of such cases where conclusive court decisions have been issued is significant, it is possible to proactively identify the customers whose filings are likely to be accepted by the courts.

Banks can then reach out to them with a solution offering similar or identical benefits to those a court decision might grant them, without going through the cumbersome and costly litigation process.

So, traditional “Law 3869” segments can be more effectively split into “Law 3869 – to be approached with the offer” or “Law 3869 – wait for court ruling”.

Similarly, this approach can be used to predict the outcomes in **France's** “over-indebtedness” (surendettement) procedure, which is centralised and run by the Central Bank (Banque de France). Predictive analytics can be used to predict the most likely outcome per filing (accepted/not accepted, and the likely amount of the new installment if accepted), as well as the likelihood of each customer respecting or not the new payment plan offered by the Banque de France.

These uses of analytics can help banks clean up their portfolios quicker.

CONFRONTING A KEY CHALLENGE

Banks possess a wealth of data that can be used for analytics, but they come from many sources and systems (from their web banking UI to print files that have not yet been digitalised!). This raises new challenges as the quality, and the format of these data requires substantial clean-up effort before they can be used for analytics.

HOW QUALCO CAN HELP:

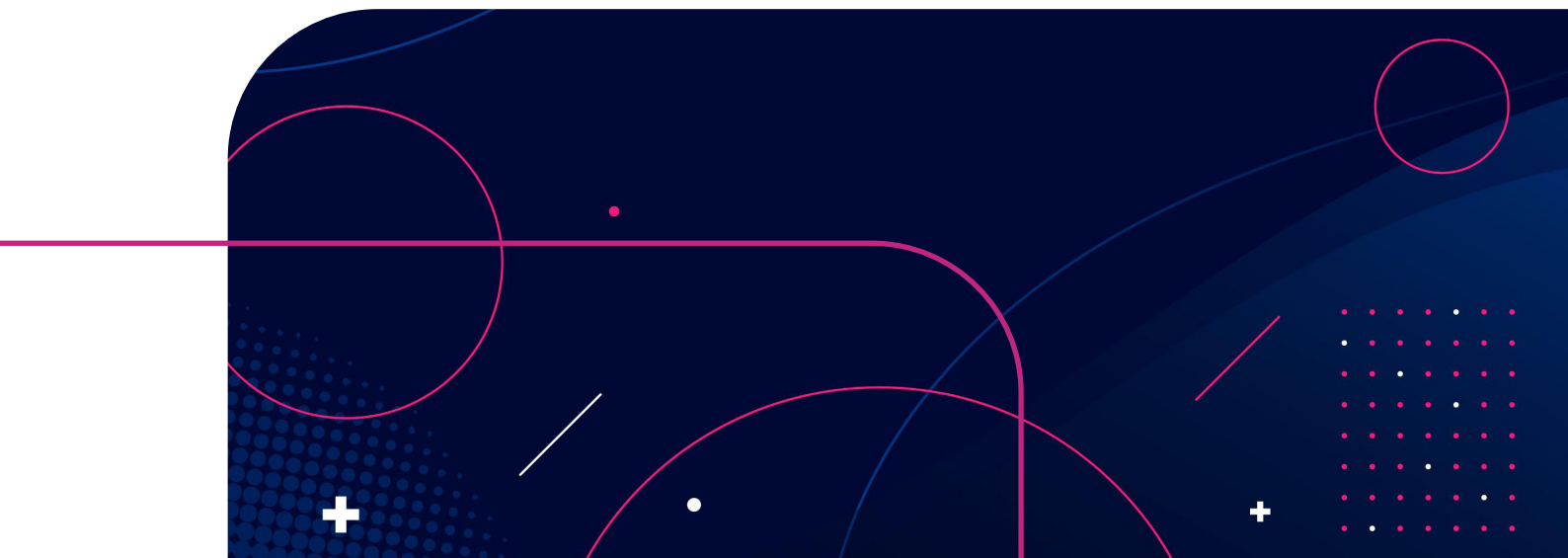
QUALCO Data-driven Decisions Engine (D3E) is a solution that automates and streamlines every stage of the analytics workflow, from data ingestion to predictive modelling, decision making and action optimisation – with end-to-end tracking and reporting at every stage of the process.

Designed for any business that manages credit, **D3E** empowers business users and analysts to design, develop and deploy strategic and operational decision-making initiatives within a single platform. Advanced analytics and machine learning enable organisations to make insight-driven decisions and ultimately transform collections operations and generate real value.

D3E offers:

- › Consolidated data view to facilitate the analytical assessment
- › Robust automation for the building and maintaining of predictive models
- › The potential to create multiple models with minimum cost
- › Identification of customer behaviour by using explainable machine learning for better segmentation
- › Optimisation at scale for multiple costly operations to become more productive

DISCOVER MORE ABOUT D3E



AUTHORS



Panayis Fourniotis Pavlatos
VP of Analytics at QUALCO
pfourniotis@qualco.eu



George Fertakis
Senior Business Consultant at QUALCO
gfertakis@qualco.eu



www.qualco.eu

