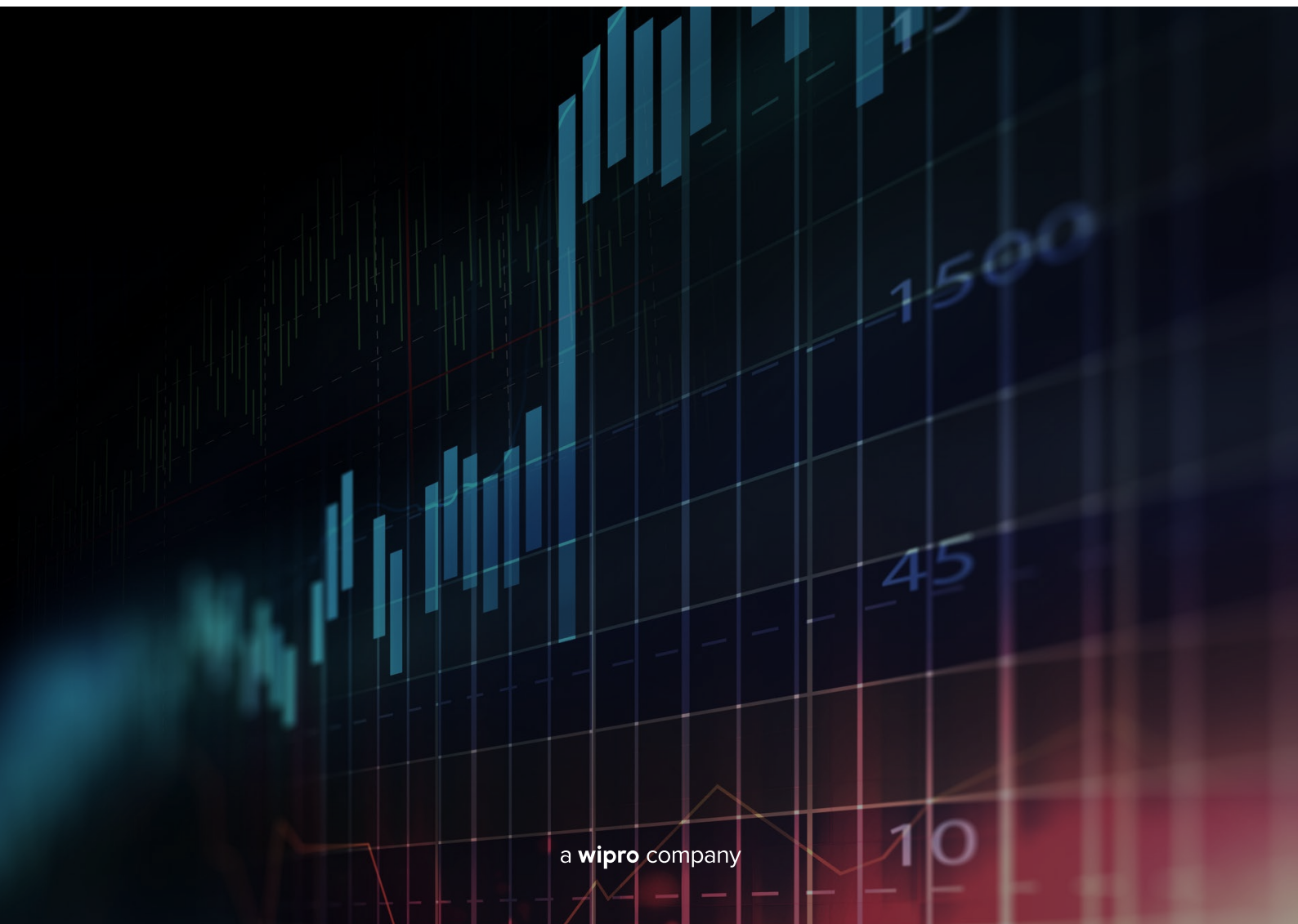


# CAPCO

## CLIENT PROFITABILITY AND PREDICTING FUTURE CLIENT VALUE

HOW CAPCO DATA SCIENTISTS DELIVERED A GLOBAL BANK OVER  
£12M IN COST AVOIDANCE AND SAVED OVER 170,000 FTE HOURS

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# INTRODUCTION

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Interest in recent years in data science and machine learning has increased substantially. The technology industry was first to adopt these approaches, but they have now entered the mainstream, with companies in all industries asking how they can make best use of the data they hold.

In financial services, there is a lot of hype about what machine learning can achieve. However, a quick search will confirm that there are very few concrete examples of it being put in practice in large financial institutions and delivering tangible results.

Here at Capco, we strongly believe that data science can add significant value in financial services across multiple functions with high returns on investment. This latest content series, 'Data Science in FS', aims to highlight the problems that Capco has worked on in the past, and how they can apply in your organization.

# BACKGROUND

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Monitoring client profitability is fundamental for any organization. Understanding client profitability and its drivers accurately can inform organizations not just which clients are profitable, but why certain clients are more (or less) profitable than others. In the short term, insights on profitability can enable tactical cost reduction by moving clients to lower cost channels, understanding which areas require automation or renegotiating pricing. In the long term, it can guide strategic growth decisions and product/marketplace segmentation.

Getting a sense of client profitability is far more complicated than using the calculated lifetime revenue from a client, or

the gross margin generated from transactions as a proxy. A thorough client profitability analysis should take into account every touch point a client has with your organization, in order to consider and assess exactly the servicing costs associated with said client.

Leveraging this data, machine learning models can then be built to forecast future client profitability, or client value. This predictive modelling can be extremely powerful and could be used to make specific recommendations and best courses of action relating to individual clients.

# THE PROBLEM

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The main problem in getting accurate information on client profitability has typically been the data siloes that exist in financial institutions between revenues (front-office) and costs (typically back-office). Furthermore, costs, especially indirect costs, can be challenging to allocate across specific clients. Combined, these problems have a couple of potentially severe consequences:

## **Unoptimized client base due to incorrect widely-held beliefs**

As a complete view of the profitability of a client isn't often available, many banks fall back on an easily available proxy: client revenue. Using revenue as a measure can work, but it often gives a skewed impression of profitability.

For example, a client with modest revenue and a simpler portfolio could be more important to focus on than a client with higher revenue with multiple complex accounts i.e., larger servicing cost base. Also, there might well be a number of clients that are seemingly beneficial for the bank but are in fact not as they necessitate a plethora of trades and are serviced via costly or manual processes.

## **Inaccurately capturing all client servicing costs**

A significant challenge in assessing client profitability is the identification and attribution of all relevant costs. In order to accurately include all costs associated with servicing clients, an organization needs to identify all channels of interaction, evaluate the costs associated with those channels, and aggregate those costs for each client.

The search for this wealth of information can be an overwhelming task, especially for larger institutions where a multitude of systems exist. Often, the data will be available, but it will frequently be aggregated into different cost categories or service areas, and so will not detail a client's individual servicing costs. As a result, attributing a cost from a manual process, for example, to a specific client can become really challenging.

Using a bottom-up approach by taking advantage of data science techniques can help to address both of these issues.

# CASE STUDY

## Approach

Capco was engaged by a global bank whose longer-term priority was to be able to predict customer value to help reduce cost and effectively prioritize the time they spent on different clients. The client had no clear grasp of the cost of client servicing operations. A team of data scientists used the following approach to enable the bank to make significant cost savings:

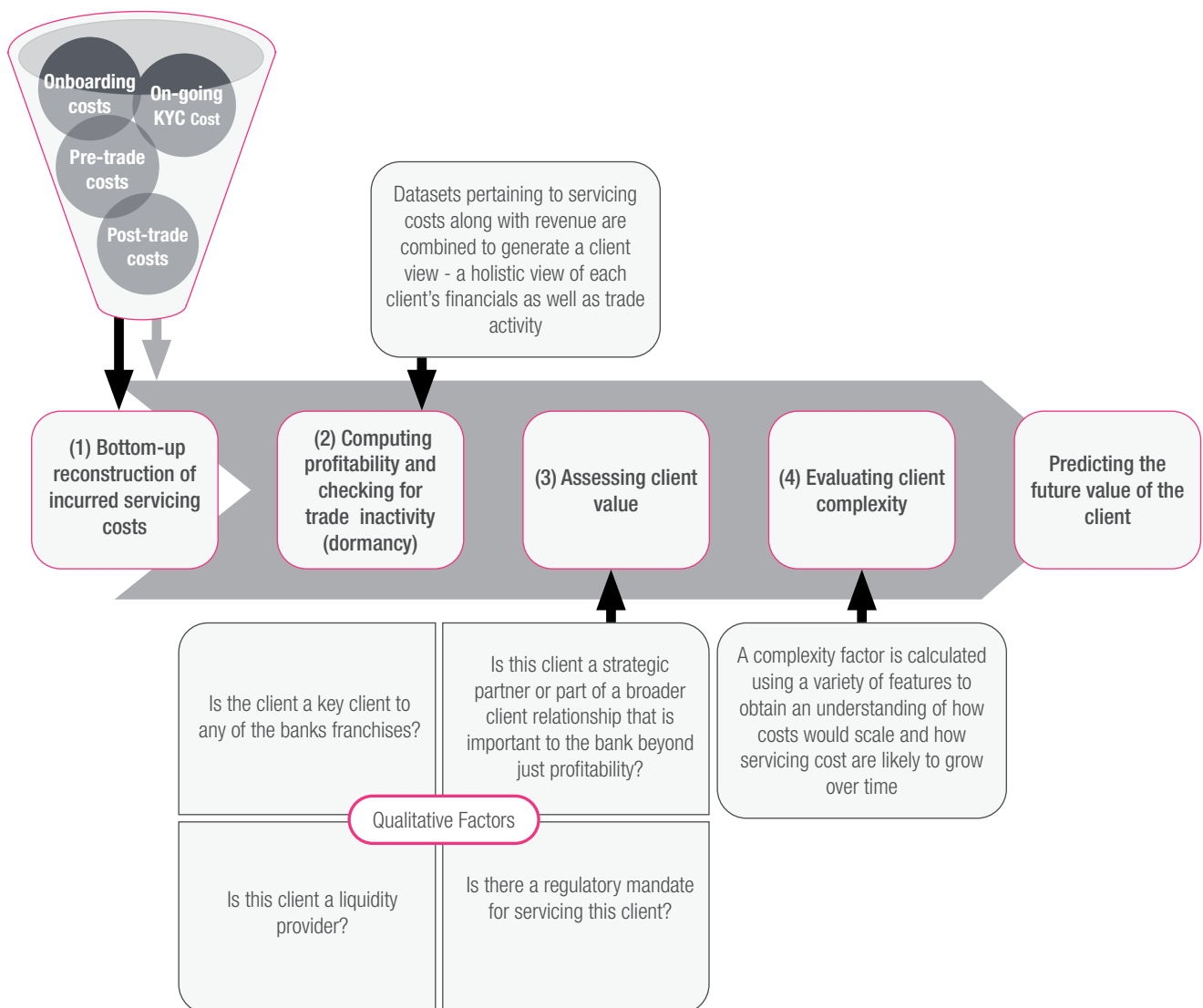


Figure 1: Overview of the client value assessment and prediction process

## 1. A bottom-up reconstruction of incurred servicing-costs

The team first identified a comprehensive list of data sets related to both pre-trade (such as onboarding and periodic KYC costs) as well as post-trade servicing costs including cost per transaction (differing by product), exception handling, manual interventions, and email queries.

The data scientists then assessed and combined the relevant data and worked to allocate costs appropriately to each client. This involved including data such as:

- Number of locations there is a business relationship with the client, to determine KYC costs
- Quantity of incoming and outgoing emails
- Number and type of funds and regulatory costs associated to them
- Cost of exceptions

## 2. Computing Profitability and Checking for Dormancy

All these data sources were combined with revenue data to generate a client persona - a holistic client view. This client view enabled the team to derive the following:

- i. Client Profitability – unless the client is strategic in some way, clients that cost more to service than they generate in revenue are of limited value
- ii. Client Dormancy – if a client is mainly dormant, then they are likely incurring cost without generating much revenue

## 3. Assessing Client Value

Profitability is a key input to value, but other factors were considered to get a complete picture of how valuable the client was to the bank. Example factors included:

- Is the client a key client to any of the bank's franchises i.e. a strategic partner or part of a broader client relationship that is important to the bank beyond the bottom line?
- Is this client a liquidity provider?
- Is there a regulatory mandate for servicing this client?

These more qualitative factors were overlayed with the client profitability in the form of scores to provide a holistic view of the value of the client to the bank.

## 4. Evaluating Client Complexity

The above analysis was useful in determining the client value at a point in time but did not give any indication as to how this value might change over time. To get a better sense of this, the team came up with a measure for client complexity which provided insights as to how the incurred costs are likely to change over time.

The complexity factor was calculated as a score, using a variety of features including the diversity and constituent parts of clients' product portfolio, number of systems on which the client uses to trade, number of business relationships across distinct jurisdictions, the client's ownership structure and more.

Using this, the team got a good handle of how costs would evolve across different products and systems. Linking this to trade volumes enabled the team to forecast how costs are likely to grow based on the increased trade activity.

## 5. Predicting the future value of the client

The team then built a machine learning model to predict the profitability of new clients to help maintain a value threshold for all clients being serviced. This machine learning model

leveraged data from the client persona and data about the new clients to compare current and future servicing costs against predicted future revenue.

To predict future revenues, the team considered historical revenues, client attributes, historical and recent product uptake, as well as the potential implications of the qualitative factors relating to complexity.

In terms of costs, all other features engineered relating to the client's complexity were factored in too. These included:

- How exceptions are likely to grow as trade activity increases?
- How costs are likely to grow and scale with increasing exceptions?
- How many more exceptions will need to be handled in downstream systems?
- What are the FTE implications of that increase in exception handling per system?

# APPLICATION AND OUTCOMES

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Applying this model allowed the bank to discover the necessary thresholds within data attributes that determined clients' commercial viability. Some of the most interesting (and some unexpected!) features which influenced the profitability of a client were:

- The combination of specific products within a client's product portfolio
  - Multi-jurisdictionality and the regulations which a client is exposed to
  - The amount of email communication with a client
  - The client's primary trading location
- The industry or industries within which a client operates
  - The channels which a client uses and the flexibility of adopting new channels
  - Whether a client has interacted with one or multiple parts of the bank

The model has been proven both to give valuable insights into the commercial viability of the business relationship and provide insights on how to improve client profitability through the up-sell and cross-sell of other products and services.



# CLIENT IMPACT

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Client profitability and modelling for future profitability allowed the client to prioritize their existing list of clients. This data allowed the client to materially reduce their pre- and post-trade servicing costs significantly, in the following ways:

1. To demonstrate rapid value, the team identified several clients whose cost to service was substantially higher than the revenue they generated. These clients were flagged to management and business execution teams, and a significant portion of these clients were offboarded.
2. A population of clients who did not need to go through the KYC refresh process were identified. These were discovered through the complexity analysis, and showed no actively traded products, and had multiple dormant

accounts or subaccounts which were incurring an annual cost to service. The team was able to reduce the KYC backlog further by identifying clients who fall into a higher risk bracket due to only a single product or clients whose high-risk accounts were dormant.

In addition, clients who were predicted to be highly profitable were steered towards the relevant teams for cross and up-sell opportunities, to enable them to meet their full potential.

The holistic view of client profitability not only saved significant time and money but also empowered the bank to substantially reduce the KYC backlog (and therefore regulatory risk). The bank saved over **£12 million** from offboarding unprofitable clients and more than **170,000 hours** (equivalent to 81 FTEs) needlessly sending clients through the KYC refresh process. This delivered a **> 2000%** ROI on the bank's investment.

## TO WRAP UP

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It is more important than ever that banks have a holistic view of the value and the complexity of each of their clients. Analyzing and predicting client profitability can help to decrease cost by informing automation efforts and optimizing the client list, and increase revenue by better focusing account management time and by highlighting desirable client attributes.

Capco can combine cutting-edge machine learning techniques with financial services expertise to help you achieve these aims. For more information on the best way to assess and predict your clients' value, get in touch with our Data Science capability lead, Riddhi Sen, on [riddhi.sen@capco.com](mailto:riddhi.sen@capco.com).



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## ABOUT CAPCO

Capco, a Wipro company, is a global technology and management consultancy specializing in driving digital transformation in the financial services industry. With a growing client portfolio comprising of over 100 global organizations, Capco operates at the intersection of business and technology by combining innovative thinking with unrivalled industry knowledge to deliver end-to-end data-driven solutions and fast-track digital initiatives for banking and payments, capital markets, wealth and asset management, insurance, and the energy sector. Capco's cutting-edge ingenuity is brought to life through its Innovation Labs and award-winning Be Yourself At Work culture and diverse talent.

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