**Capstone Project**   
**Project Report**

**May 2023**

Word Count: 5,000 words

**Introduction**

**Core Objectives**  
The core objectives for the Capstone project was to mine data in order to create a tool for Credit Unions (and banks) that will evaluate customers credit worthiness based on an ethical standardised criteria that is transparent to all.

We explored why this was necessary and explored how important it could be to the business Our focus is on helping Credit Unions have a stronger online presence as the banking sector has been changing rapidly and moving online and Credit Unions are currently behind in the market in this regard (Gov.ie, 2019).

This tool would help automate the credit approval process, reducing the underwriting time and allow customers to get answers quicker in regards to the potential of securing a line of credit. All this in just a few clicks or taps of the finger.

**Role & Responsibilities**

Before we could split our any particular roles and responsibilities we as came together as a team came together started out assessing the project in class to determine the type of business we were considering and what makes most business sense for a potential project. Wat this point we both worked together on the strategic report to define key business objectives and how we were going to achieve this and what data sets could be used. The project was done very much in a TagTeam format whereby each of us cross checked and sense checked the approach from phase to phase.

**Key tasks throughout the project (who worked on what)**

* We both worked on defining what the project was.
* We both worked on the strategic document (tag team effort).
* Subsequent to this we both searched for data sets that might work for this type of project however Rylee sourced the core data set from which we based our project on.
* Data preparation was undertaken by Rylee and Mario (50-50 split)
* Date processing and data visualisation – again both of us worked on this (50-50 split).
* We also had regular check-ins to ensure the project was on track but also trouble shoot issues that we were having with on the data set.

**Cross Industry Standard Process**

The Cross Industry Standard Process for Data Mining or known as the CRISP-DM is a model or methodology that helps standardise the data science process. It has six distinct phases and are as follows:

1. Business Understanding

2. Data Understanding

3. Data Preparation

4. Modelling

5. Evaluation

6. Deployment

In the subsequent pages we will delve more into how we mined our data.

**Business Understanding**

This section explores what exactly is needed by the business in terms of data analysis. As outlined in our strategic analysis document – our core objectives were **t**o create a tool for Credit Unions (and banks) that will evaluate customers credit worthiness based on an ethical standardised criteria that is transparent to all. There is a competitive advantage to be gained by the credit unions such as:

* Provide a stronger presence in the online banking sector
* Transparency attracts more customers due to increased trust
* Increases customer satisfaction (personalised)
* Increases customer retention
* Broader customer access to credit
* Fairer loans minus bias and discrimination

**Market gap here in Ireland**

We also identified that there is a market gap here in Ireland. KBC and Ulster bank left the Irish market 2023 there are only three large banks now in Ireland, providing an opportunity for the credit union to grow their offering.

**Future focus**

AI technology can be used to help implement an unbiased approach to credit rating and in turn can optimise and speed up the process. It can result in tailored bespoke loans. This type of approach is based on inclusive-led AI technology which could be used by credit unions/banks.

A project must be viable to the business from the outset otherwise it will not make financial sense to undertake in the first place.

**Data Understanding**

So what data do we have access to and what needs to be done to ensure that its relevant to how we need to use it.

To begin, we analysed data derived from the decision making process of credit approvals provided by a German bank. This dataset is available on the UCI MachineLearning Repository website (Hofmann, 1994). After performing EDA on the data, we wanted to create a predictive model based on the approvals and denials contained in the dataset.

With this predictive model, customers will be able to determine the probability of being approved while also providing clarification as to why they would be a strong or weak candidate and offer tips as to how it could be improved based on the areas that were lacking.

*‘AI credit scoring decisions are based on a lot of data, such as total income, credit history, transaction analysis, work experience, and even Google Analytics. In essence, scoring represents a mathematical model based on statistical methods and accounting for a large amount of information. As a result, credit scoring using AI provides more sensitive, individualized credit score assessments based on an array of additional real-time factors, giving access to finance to more people with income potential’* (datrics, 2023)*.*

By widening the fields of data that is collected we also expand our data set to look at patterns to consider customers credit rating on a much wider level, not just by credit history, loan paybacks and income.

The different types of data mined can be as follows:

* Historical data
* Digital footprints
* Predictive analytics
* Alternative data (shopping history, property records, spending habits)
* Realtime transactional data

The data that we had sourced is relevant and key to understanding and also delivering on why this project makes business sense for the credit unions.

This phase of the project was about collecting the data set, examining the data to ensure its relevant to the project but looks at the various properties through the set, an even deeper dive into the data set, documenting any issues with the data and really examining it to ensure we could work with it. We had to examine what was missing and why but also determine any attributes that may be irrelevant to us. We couldn’t progress into data preparation without examining our data set in-depth.

**Our datasets**  
The first data set that we had sourced was useful to the project but we quickly discovered that it was an object based dataset and when we examined it closely we just couldn’t work with it. It simply would not provide an accurate data visualisation project for us to work from. As a result we had to locate a second data set. This was taken from the same source but was a numerical version which had 27 columns.

This particular dataset was something we could work with because XXXXXXXXXXXXXXXXXXX.

**Our dataset findings were as follows:**

1. On the numerical dataset as the whole first column was not a number NAN
2. There was no correlation between the last five attributes.
3. There was no missing data
4. XXXxxxxxxxxxxxx
5. Xxxxxxxxxxxxx
6. Xxxxxxxxxxxxxxx
7. XXxxxxxxxxxxxxxx

**Data Preparation**

This phase was all about preparing the data for modelling. This went through a number of process and phases to ensure our data could be used and definitely was the longest section of the project. This part of the project covered off a number of areas including:

* Inspecting and cleaning the data
* Constructing the data
* Integrating the data
* Formatting the data

**Inspecting and cleaning the data**

As mentioned on inspection of the data we removed the first column as that was NAN.

We also dropped the last five attributes (column 21–27) as there was no way of filling this information as it may skew the data.. Then we started the process of looking for correlations, and looking for which columns will be useful to help generate visualisations from. We need to ascertain which columns to related to different columns to give some useful data to mine. These are as follows:

* XXXXXXXXXXXXX
* XXXXXXXXXXXXX
* IXXXXXXXXXXX
* XXXXXXXXXXXX
* XXXXXXXXXXXX
* XXXXXXXXXXXX
* XXXXXXXXXXXX

**Constructing the data**

We also then constructed the data into a format that we know would provide optimal results. XXXXXXXXXXXXXXXXXXXXX

**Integrating the data**

We also integrated another data set XXXXXXXX

**Formatting the data**

Lastly we formatted the data XXXXXXXXX

**Modelling**

Once our data set was ready to go we could then start the modelling phase or creating diagrams of the data. We did this by XXXXXXXXXXXXXXXXXX

**Evaluation**

For the evaluation of the data we needed to check the quality and reliability of the data, sort through and then classify the data, and following this perform tests and cross check the results.

**Deployment**

Xxxxxxxxxxxx

**Conclusion**

Following the processing and visualations of our capstone project we conclude that:

* Xxxxxxxxxxxxxxx
* Xxxxxxxxxxxxxxx
* Xxxxxxxxxxxxxxx
* Xxxxxxxxxxxxxxx

**Appendix**

Evidence of group work.

**Group Reflection**

Xxxxxxxxxxxx

# References

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