Analysing how Financial and Demographic Factors Influence Mortgage Lending Decisions

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Abstract

This research investigates the factors influencing mortgage lending decisions, focusing on financial and demographic factors. Using data from the Home Mortgage Disclosure Act (HMDA), regression analysis and feature selection, and aim to uncover disparities in loan approval rates and amounts among demographic groups. The study addresses gaps in research by examining the interactions between financial and demographic factors and loan characteristics in mortgage lending. By identifying patterns of discrimination and barriers to credit access, contribute to promoting fairness and equity in lending practices. This research may inform policy recommendations to address biases in mortgage lending.

Keywords: Mortgage lending, HMDA, socio-demographic factors, ensemble modelling, feature selection, discrimination

1. Introduction

In today's society, addressing discrimination, particularly in crucial areas like mortgage lending, remains a pressing concern. Many American families rely on mortgages to purchase homes, reduce housing expenses during periods of low interest rates, and leverage home equity for various purposes, such as investigating in education or small business. However, not all families have equal access to mortgage credit. Demographic factors such as racial and ethnic, financial factors such as income and lien status disparities in mortgage lending contribute significantly to the considerable gaps in homeownerships and wealth.

Martinez and Glantz (2018) analysis of mortgage data highlighted significant disparities in access various metropolitan areas, the study revealed that African faced less mortgage approvals compared to white borrowers. Similarly, research by Bhutta and Himzo. (2020) found that Black mortgage applicants encountered twice denial as white applicants to have their application by lenders, and black and Hispanic borrowers pay higher interest rate than non-Hispanic borrowers. More recent research, by Blattner and Nelson (2021), has emphasized the notable impact of credit scores on disparities among social groups. This study revealed that statistical noise in credit scores disproportionally affects historically disadvantaged consumers, including minority and low-income individuals.

These findings suggest that there are disparities in access to credit and opportunities among different demographic groups. Therefore, conducting a comprehensive analysis of the latest mortgage lending data, focusing on the influence of financial and demographic factors on loan approval amounts, is crucial for understanding and addressing these disparities. This analysis will contribute to promoting fairness, equity, and transparency in lending practices.

The research to analyse the factors, influencing mortgage lending decisions, particularly focusing on financial and demographic factors. Discriminatory practices in mortgage lending have long been documented, highlighting disparities in access to credit and opportunities among different demographic groups. Understanding and addressing these disparities are essential for promoting fairness, equity, and transparency in lending practices.

A law known as the Home Mortgage Disclosure Act (HMDA) was passed in the US in 1975, with the goals of increasing mortgage availability and guaranteeing fairness in lending. Banks are required to exchange data regarding the home loans they make.

Research Question. To what extent do financial and demographic factors influence loan approval amounts in the United States?

The proposed solution involves conducting a comprehensive analysis of the latest mortgage lending latest data, which is from 2022, focusing on the influence of financial and demographic factors on loan approval amounts. This analysis will utilize advanced statistical methods, including regression analysis and machine learning algorithms, to examine patterns and relationship within the data. By examining the influence of financial and demographic variables, the study will contribute to a deeper understanding of the dynamics of lending practices in the United States and will identify any disparities or biases in loan approval amounts across different demographics. As below described the structure of the document with key argument points interpreted in each section.

The literature review will introduce previous research, critically compare key arguments from different studies, and identify gaps in existing literature. By doing that, will be able to find a highlight of the research niche and justification of importance of study. Proper citation of previous works will ensure academic integrity and demonstrate understanding of the field. This process will provide a solid foundation for the research and contribute to advancing knowledge in the field.

In the research method and specification section, will outline the proposed methodological approach, detailing the steps and activities necessary to complete the project. The plan to answer the research question and support claims will involve providing experimental evidence to demonstrate the effectiveness of the approach. Additionally, will critically assess ethical issues such as privacy, biases, and data usage ethics, and detail measures to address to address them responsibly. This comprehensive approach ensures the integrity and validity of the research while upholding ethical standards.

2. Literature Review

The literature review will begin by examining previous works that contribute to understanding of fair lending practices in mortgage underwriting decisions. Key areas of focus will include the impact of applicant characteristics (income, lien status, race/ethnicity, gender, and age) on lending decisions, as well as the significance of HMDA data in identifying disparities in mortgage lending. The review will also discuss the limitations of HMDA data and the potential for predatory lending practices in mortgage scenarios.

2.1 Impact of Applicant Characteristics on Lending Decisions

A study by Lindsey-Taliefero and Kelly (2021) examined the underwriting decisions of reverse mortgages to determine if race/ethnicity, gender, or age were significant factors. The study used loan-level data from the expanded 2019 Home Mortgage Disclosure Act (HMDA) and found statistically significant lending disparities based on applicant race/ethnicity, gender, and age. This finding contributes to identifying disparities in reverse mortgage lending and highlighting deficiencies in the HMDA data. The study employed a logistic regression model to estimate the denial/approval decision. This method is well-suited for analyzing binary outcomes, such as approval or denial, and provides measures of model fit and classification accuracy, including the omnibus test of model coefficients, pseudo-R squared, and area under the receiver operating characteristic (ROC) curve.

However, logistic regression has limitations. It assumes a linear relationship between independent and dependent variables, and its predictions may be inaccurate if this assumption is violated. Additionally, it may not perform well with small sample sizes or high multicollinearity among predictor variables. Researchers should be mindful of these limitations when interpreting the results, particularly in the context of the specific dataset and predictors used.

2.2 Algorithmic Fairness in Mortgage Lending

Das, Stanton, and Wallace (2023) explore algorithmic fairness in credit scoring, particularly focusing on biases in the US mortgage market. They discuss human versus machine bias, bias measurement and attributes, group versus individual fairness, bias stages, and value systems. The literature emphasizes assessing bias at both group and individual levels and understanding the value systems supporting fairness. Das et al. (2021) and Vasudevan and Kenthapadi (2020) provide metrics for detecting bias in datasets and stress fairness constraints in algorithmic modeling. Group fairness aims to prevent discrimination across demographic groups, while individual fairness seeks to treat each person fairly based on their unique characteristics. The study employs machine learning models on a randomized sample of 500,000 mortgage applicants using the AutoGluon library from Amazon Web Services. Focusing on maximizing the F1 score, they demonstrate the effectiveness of ensemble ML models over logistic regression, highlighting significant minority bias. Ensembling ML models can handle complex data relationships and often outperform simpler models like logistic regression. However, comparing outcomes may not be suitable due to computational resource requirements and the potential loss of meaningful patterns when randomizing datasets. Changing the seed number for randomness can affect accuracy.

2.3 Identifying Disparities in Mortgage Pricing

Bhutta and Hizmo (2020) merged Federal Housing Administration (FHA)-insured mortgages data from 2014 and 2015 with HMDA data from 2013 and Optimal Blue, a company which offers a software platform to mortgage lenders for use during the interest rate lock process. The study uses a unique loan-level dataset covering hundreds of lenders across the country, with rich details for each loan, including demographics, underwriting variables, and detailed price data, and investigated racial discrimination within the mortgage pricing such as interest rates, discount points and fees. The study reveals statistically significant disparities in interest rates among different racial and ethnic groups. However, these differences are compensated by variations in discount points, suggesting that interest rate gaps may not necessarily indicate discrimination but rather reflect varied borrower preferences. In previous papers, Woodward (2008) analyzed FHA loan pricing in 2002, revealed that minority borrowers had higher interest rates and pricing disparities, and Barlett *et al*. (2019) identified interest rate gaps between minority and white borrowers.

By critically contrasting these works, it becomes evident that the current study contributes to the literature by providing a comprehensive analysis of the trade-off between interest rates and discount points, particularly in the context of minority borrowers. One benefit of this, the study’s method of using ordinary least squares

(OLS) regression analysis how it controls possible influences from other factors making the findings stronger and reliable. Additionally, including different variables like credit scores and borrower characteristics gives more detail of how mortgage pricing works for different people. Also, the study focuses on a specific group of loans during a particular time, so cannot assume that the findings apply to everyone in all situations.

2.4 Recent Trends in Racial Disparities

Bhutta, Hizmo, and Ringo (2022) used HMDA data for 2018-2019 and found that the factors like racial and ethnic disparities denied, and conclusively observation for racial based decision appeared below than previous research. Previous papers such as Munnell *et al.* (1996) showed that denial of Black and Hispanic applicants over rejected roughly 8 percentage, and a few studies examined denial gaps and discrimination. Moreover, Bartlett *et al.* (2022) discovered that denial rates increase by 7-10 percentage points. However, their study couldn't consider applicants' credit scores because they relied on public HMDA data. Similarly, Kopkin (2018), found that where people live affects whether they're denied conventional mortgages, likely due to underlying racial biases in those areas. Park (2021) explored if economic stress could explain why certain racial groups face more loan denials. Lastly, Giacoletti *et al*. (2021) noticed that Black borrowers tend to secure loans towards the end of the month. They theorized that this might be because loan officers, striving to meet monthly quotas, are less discriminatory during this time.

The current study employed quantitative analysis and statistical default regression models for credit risk of loan, to determine if the loan has low enough risk to warrant approval and whether its eligibility for the program is under consideration. Even though the study gives key info, it has downsides. Relying just on home loan application info might miss parts like the traits of the borrower or the features of the area that affect loan choices. As it is difficult to prove direct cause, it is vital that this study is careful with its findings such as bias and other factors besides unfair treatment.

2.5 Misidentification of Race and Ethnicity

Dobre and Witzen (2023) used Bayesian Improved Surname Geocoding (BISG) probability for race and ethnicity and discovered that race identified by lenders is more strongly associated with BISG probabilities of race using from HMDA 2018 to 2021. They demonstrated that lenders often misjudge how likely someone is to be a certain race, especially for people who are probably Black or Hispanic. Also, the number of mistakes goes down when the person applying for a loan and the loan officer are of the same race. For instance, Saperstein (2006) looked at how the public and surveyors see race differently, finding that "White" and "Black" match up but not "Other." Magana *et al.* (2016) found big gaps between what people say their race is and what their health records show, most in Hispanic patients. It checks if loan givers show a "same-race lean," which is how the public tend to see faces of their own race more. Additionally, evidence suggests that interviewers, particularly White ones, may record darker skin tones for similar subjects, indicating potential biases in racial classification (Hannon and DeFina, 2014).

While BISG is a widely used method for predicting race and ethnicity based on surname and geography, the higher correlations observed between lender-identified race indicators and BISG probabilities suggest that surname and geography may influence lenders' racial classifications, but other unobserved factors could confound these results. The accuracy of BISG predictions may vary across different racial and ethnic groups, leading to potential biases in the analysis.

2.6 Counterfactual Fairness for Fair Lending Models

A study explores issue of unfairness in mortgage lending, particularly its impact on racial and ethnic groups Ghoba and Colaner (2021), and it aims to address the problem using counterfactual fairness to train fair machine learning models. Created balanced dataset, isolating the race variable to demonstrate unfairness. in mortgage approval and interest rates between African American and non-Hispanic White sub-populations. To measure and mitigate algorithmic bias, researchers have introduced various fairness metrics (Kleinberg *et al.*, 2018; Verma and Rubin, 2018; Mehrabi *et al.*, 2021), including both group and individual fairness metrics. Counterfactual fairness stands out among individual fairness metrics due to its ease of use and ability to provide insights into cause-and-effect relationships (Hardt *et al.*, 2016; Chouldechova, 2017; Kusner *et al.*, 2017; Makhlouf *et a*l., 2020). The current study investigates fairness in loan approval algorithms. It tests various methods, finding removing race data improves fairness metrics, especially for interest rates. However, the study acknowledges limitation, algorithms may not achieve perfect fairness, and the chosen metrics may not capture all aspects of bias. Overall, the study offers valuable insights but highlights the need for further research on robust methods to tackle algorithmic bias.

2.7 Machine Learning in Mortgage Lending: Uncovering Bias and Advancing Prediction

Application of machine learning techniques, specifically deep learning, feature selection, and model bias investigated by Hodges *et al*. (2024), using HMDA data from 2007 to 2017. As suggested by Fishbein and Essene (2010) on HMDA data, how it can improve. Bhutta *et al*. (2017) conducts exploratory data analysis on HMDA but refrain from developing inference models, while Lai *et al*. (2023) proposes an ordinary least squares regression model using HMDA data and CEO confidence as predictors, offering a predictive framework for loan outcomes. Gender's role in financial decisions (Agha and Pramathevan, 2023), using traditional methods unlike machine learning approaches. The current study reveals that, machine learning models can incorporate gender and race into loan decisions, potentially violating lending regulations. This highlights the need for stricter oversight and algorithmic fairness considerations. Additionally, machine learning offers greater predictive power compared to traditional approaches. In conclusion, this research makes a significant contribution by using machine learning to uncover potential bias in loan approvals. However, further validation is crucial before deploying such models in real-world lending decisions to ensure fairness and ethical implementation.

2.8 Loan approval using Machine Learning approach

A study assessed machine learning models for loan approval, in order to proceed it, firstly preprocesses the data and then log transformation and scaling by Viswanatha *et al.* (2023). And then trained multiple models such as KNearest Neighbors Classifier, the Decision Tree Classifier, the Random Forest Classifier, and the Gaussian Naive Bayes Classifier. Resulting that, Random Forest outperforms loan approvals on the features. Supriya and Pavani (2019) preprocessed data, identified relevant features, and used a decision tree model, suggesting the use of multiple techniques for better results. Another study Ashwitha *et al*. (2022) employed data cleaning, exploration, and feature engineering, finding the Naive Bayes model to be most effective. While the current research mentions EDA, including key findings from EDA would enhance the understanding of dataset. And the paper lacks details on how missing values were imputed and why certain preprocessing techniques were chosen. As well as accuracy is a common evaluation metric, but precision, recall, or F-1 score, especially if the dataset is imbalanced its advisable. To gain a deeper understanding of model performance, it's crucial to choose relevant evaluation metrics and compare their outcomes.

2.9 Variable selection and machine learning

A paper discusses that variable selection, and machine learning techniques such as decision trees, support vector machines, neural networks, deep learning to get higher accuracy by (Varian, 2014). It involves, countless methods for feature importance and it gives similar results, among them the Lasso and Bayesian techniques were preferable. Previous research by Munnell *et al*. (1996) employed logistic regression, revealing that statistically significant negative association between race and loan approval, indicating that Black applicants were less likely to secure a mortgage. More recently, Howard and Bowles (2012) identified that random forest is most powerful model nowadays. The current study investigates whether a single, highly important feature can explain most of the data variation. It finds that excluding this feature has minimal impact on the accuracy of the tree-based model. There is a chance that racial discrimination as explained elsewhere in mortgage lending or included variables in the modelling highly correlated with race. Given the use of big data in this study, a deeper exploration and explanation of these findings is warranted. Additionally, while random forests can perform variable selection, the specific steps employed in this study require further clarification. While the approach may be novel, it should be presented in a clear and understandable manner.

2.10 Default prediction using Random Forest and Decision trees

The paper aimed to address increasing loan defaults using machine learning model for loan prediction. And Random Forest (RF) and Decision Trees were compared, resulting in RF outperformed Decision Trees with a higher accuracy score by Madaan *et al*. (2021). Lin Zhu *et al*. (2019) concluded that random forest has much better accuracy (98%) than other algorithms like logistic regression (73%), decision trees (95%), and support vector machines (75%). The results of Ghatasheh (2014) concluded that the random forest algorithm is one of the best options for credit risk prediction. Making loan prediction models more accurate involves several improvements. First, better data and feature design are crucial. Second, choosing the right model and combining multiple models can boost accuracy. Third, it's important to understand how the models make their decisions to ensure fairness and build trust. Additionally, addressing data imbalances and potential biases is essential. Finally, using more data sources and creating models that can adapt to changing conditions will make them more reliable in the long run. By focusing on these areas, researchers can create loan prediction models that are more accurate, fair, and useful for the financial industry.

3. Research Methodology & Specification

The proposed methodological approach to the research involves using feature analysis, including regression analysis and ensembled machine learning models to examine patterns and relationships within the data, particularly in the context of mortgage lending. The expected steps/activities planned to be carried out to bring the research project to completion during the third semester include:

A. *Data collection and preprocessing:*

"Home Mortgage Disclosure Act" by the Federal Financial Institutions Examination Office (FFEIC) outlines the structure and content of the HMDA dataset, providing explanations of the variables. For this research, the latest dataset for the year 2022 will be employed. The study demonstrates various analytical approaches, including preprocessing techniques. It covers various preprocessing steps, such as managing missing values as demonstrated by values (Bhutta, Hizmo and Ringo, 2022). Additionally, previous researchers such as Pillai *et al.* (2020) conducted statistical analysis, calculating mean, median, mode, and standard deviation to assess the distribution. They also encoded categorical features into numeric values using one-hot encoding technique, followed by normalization of continuous variables to a range from 0 to 1. As recommended by previous papers, missing values and outliers will be handled first, followed by variable normalization.

B. *Feature selection:*

The random forest regression model is effective for identifying highly correlated variables to the loan amount. It handles high-dimensional datasets seamlessly, managing missing data without the need for imputation. With its ability to handle both numerical and categorical features, it doesn't require feature scaling or one-hot coding. Each decision tree in the forest is trained independently, allowing for efficient processing of large datasets. Supervised learning enables it to make predictions from labelled data. Compared to other algorithms, random forest requires less training time and delivers accurate predictions, as demonstrated by Varian (2014). Feature importance scores provided by random forest highlight significant predictors, aiding in variable selection.

C. Dataset Fairness:

If a dataset disproportionately represents certain groups or excludes others entirely, the resulting model may struggle to generalize to unseen data. This can lead to inaccurate predictions and unfair decisions that disadvantage underrepresented groups. As suggested by (Das, Stanton, and Wallace, 2023) gender imbalance group metric is 0.45 for gender, that means cannot estimate female applicant correct. While mortgage datasets may contain a large number of applicants, a significant issue arises when the distribution of classes is uneven. This is known as class imbalance. For instance, the number of loan rejections might be much smaller compared to approvals. By creating training datasets with balanced numbers of applicants from different groups, can ensure the model learns from all populations fairly. Techniques like oversampling (replicating data points from minority groups) or undersampling (removing data points from the majority group) can be used to achieve a more balanced training set.

D. Ensemble modelling:

Employing models such as multiple Linear Regression, Random Forest, Neural Network, and Support Vector Machines for ensemble modelling to increase effectiveness and accuracy, predicting loan amount in mortgage data. Previous researcher Kumar *et al*. (2020) explored that various machine learning models like Support Vector Machines (SVMs), Random Forest, and Neural Networks. The approach goes beyond predicting the loan amount, it also aims to capture the distribution of loan amounts providing valuable information about the range and likelihood of different loan sizes. As they found, machine learning model typically require large dataset for optimal performance, since the year of HMDA dataset contains seventy-one features and ten million rows, and it is sufficient enough to get result. Evaluate how this technique compares to simpler models like multiple linear regression in terms of Mean Squared Error (MSE) and Root Mean Squared Error (RMSE), which measure the average squared difference between the predicted values and the actual values. Lower values indicate the model's predictions are closer to the real observations. Will consider cross validation techniques to ensure the model generalizes well to unseen data and avoid overfitting.

The reason chose these models:

1. Multiple linear regression: Provides a baseline and offers interpretability regarding the influence of individual features on loan amounts.
2. Random Forest: Less prone to overfitting and handles missing values well, often achieving reliable performance on various datasets. According to (Madaan *et al*., 2021), emphasized the strengths of Random Forests, like robustness to missing values and overfitting, which are valuable qualities for building a loan amount prediction model using HMDA data.
3. Neural network: Captures complex non-linear relationships between features in the HMDA data that might influence loan amounts. According to (Hennigan and Hanson, 2021), it highlights the effectiveness of Neural Networks in handling complex loan-related data.
4. Support Vector Machines: Effective in handling high-dimensional data (like HMDA) and can be robust to outliers. According to (Akça and Sevli, 2022), this paper demonstrates the suitability of SVMs for loan prediction tasks, particularly when dealing with datasets that might have limited samples. HMDA data can be vast, but depending on the specific subset, SVM's ability to handle smaller datasets could be beneficial.

Those factors can justify the reason.

E. *Tool and Test data:*

Tool: Python is a popular choice for machine learning due to its extensive libraries and community support. Libraries like Scikit-learn provide implementations for various algorithms as mentioned section 3D (Linear Regression, Random Forest, SVM). TensorFlow or PyTorch are powerful libraries for building and training Neural Networks. Frameworks like Scikit-learn and TensorFlow offer a higher level of abstraction, making it easier to build and manage machine learning pipelines, including data preprocessing, model training, and evaluation. Cloud platforms like Google Colab or Amazon SageMaker provide virtual machines with pre-installed libraries and resources to handle computationally expensive tasks like training Neural Networks.

Test data: According to (Park and Ryu, 2021), they sampled HMDA data to 30% and 70%. Since the dataset is large, a simple holdout method with a sizable holdout set (20-30%) is typically sufficient for evaluation, as done by previous researchers.

F. *Evaluation:*

As discussed in section 3E, train the ensemble model on the training set, and evaluate its performance on the unseen holdout set using the metrics mentioned in section 3D. Also, R-squared metric indicates how well the model explains the variance in loan amounts within the holdout set. However, a high R-squared does not necessarily guarantee a good model (e.g., overfitting). As well as the evaluation will be based on fairness metrics at both group and individual levels as mentioned section 2.2 (Das, Stanton and Wallace, 2023) review. This will involve comparing the machine learning model's predictions assessing the explanatory power of the model. Explanatory power refers to how well can understand the reasons behind the model's predictions. In loan amount prediction, this means understanding how different features in the HMDA data (e.g., borrower income, loan type) contribute to the predicted loan amounts.

G. Ethical concerns:

This project proposes using ensemble modelling to predict loan amounts based on public anonymized HMDA data. While public data offers accessibility, ethical considerations remain crucial for responsible use. The model's predictions should be a guide, not the sole factor for loan approval. Human expertise and a focus on fair lending principles, as outlined by regulations like the Fair Housing Act (FHA), remain essential components of the loan approval process. This safeguards against potential algorithmic discrimination based on the model's predictions. Clear guidelines for responsible model use will be established. These guidelines will emphasize human oversight alongside the model's predictions, ensuring fair and ethical lending practices. By acknowledging these ethical considerations and implementing appropriate safeguards, can leverage ensemble modelling for loan amount prediction in a way that complies with relevant regulations and promotes equitable lending practices.

E. Project Plan:

In Figure 1, a Gantt chart is plotted for the capstone project semester.

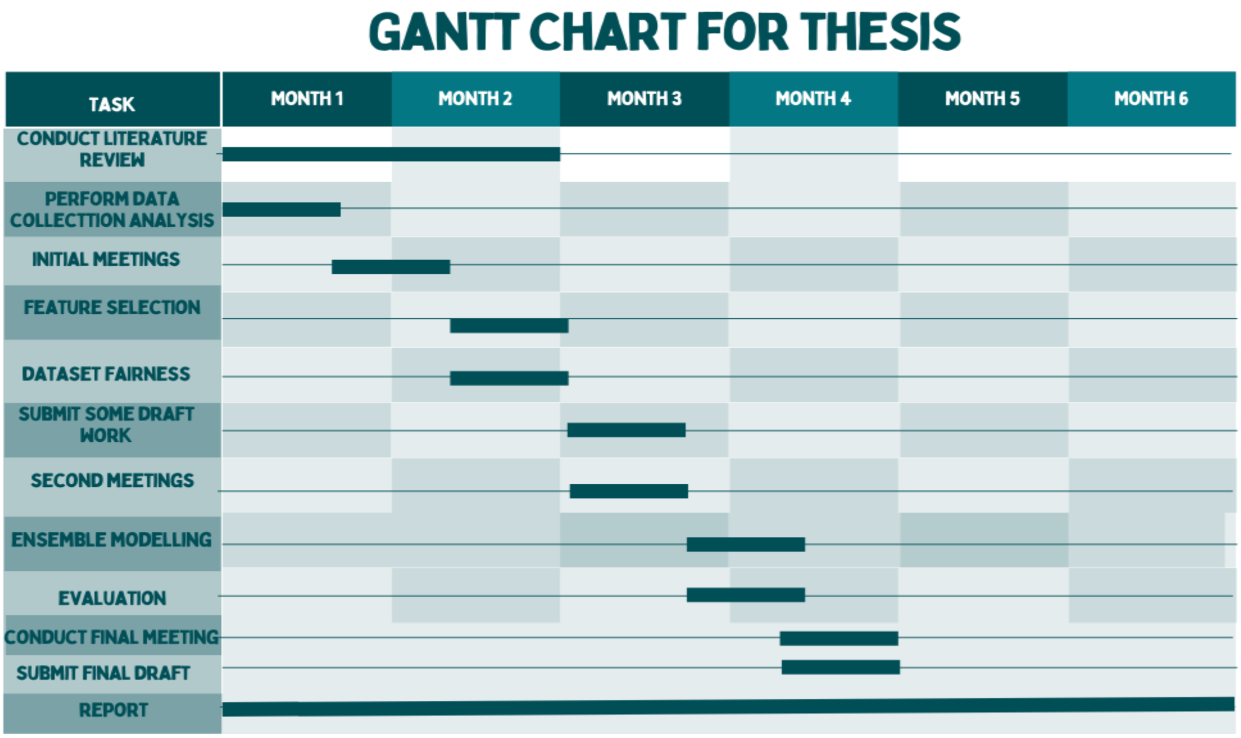

Figure 1 Gantt chart for thesis

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