Model Development: Learnings taken from building models in a developing country.

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Introduction

The objective of my presentation is to highlight the learnings gained through building Acquisitions Models in a Developing Economy.

Three key topics will be covered:

- Reject Inference
- Debt Restructuring
- Variable Bias

A few things about WesBank

- WesBank is a division of FirstRand Bank, which is one of the Big Four Banks in South Africa.
- WesBank is the Vehicle Asset Finance Product House within the First Rand Group.
- WesBank and its associate brands (TFS and VW) currently has about 60-65% of the VAF market share in South Africa.
- WesBank does not only do vehicle finance, we also finance:
  - Anything with wheels – Bicycles, Caravans, Trailers, Farming/ Building Equipment etc.
  - Recently started financing Solar Panels.

Overview of South Africans Credit Landscape

Population

- There are 60.6mil people in South Africa, of which 40mil are of adult age and less than half are Credit Active (+/- 18mil).
- Average monthly income in South Africa is R25 000 per month.
- Population Inequality.

Credit

- Average loan values: Home Loan = R1.5mil, Vehicle Loan = R300k, Unsecured Credit = R40k.
- Approximately 70% of credit applications are declined across all products.
- Main reasons customers are declined: Risk, Affordability, Loan to Value (Secured) or Debt Restructuring (Unsecured).
- Max interest rate 24% per annum.
- Variable Pricing.

Bureau

- There is a Rich Source of Credit Information available on customers.
- Bureaus keep positive and negative information.
- Newly opened accounts or closed account information is updated daily and all other account information is updated monthly.

Macros

- Inflation has been above target range for the past 18 months, however finally back in range.
- Prime Interest Rate has climbed steadily over the last 18 months from 7% to 11.75%.
- Load Shedding.

Section 1

Reject Inference

Reject Inference

- Reject Inference plays a big part in Acquisition Modelling in South Africa, with approx. 70% of customer credit applications declined.

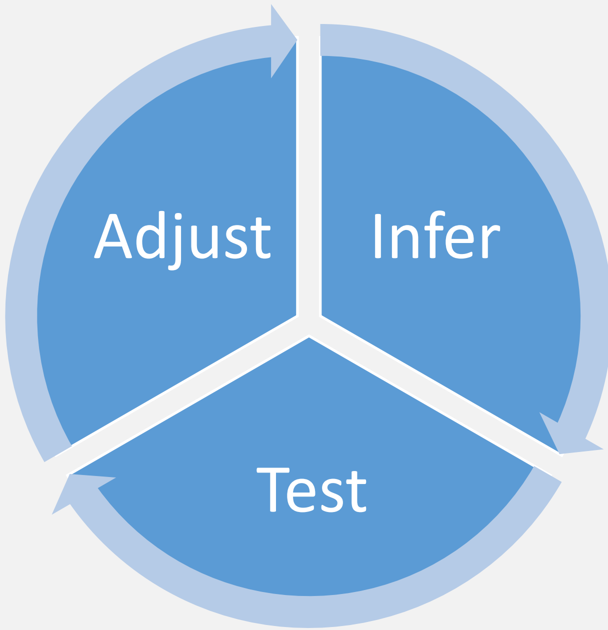
Our Biggest Concern is Balance:

- Under-inferring and the risk of swap in's might not be assessed correctly.
- Over-inferring and training a model that separates better on rejects than accepts.

Reject Inference – how this is done

1. **Control Metrics:**
   - Limits on ratio of Inferred Bad Rate to Known Bad Rate (Inf BR Range 1.5-4 times KBR).
   - Limit on Gini lift of AGB model to KGB model (<=30%).

2. Practically - A lot of time is spent determining what influence and/or what portion of the rejects should be included in the model development through iterative adjustments.



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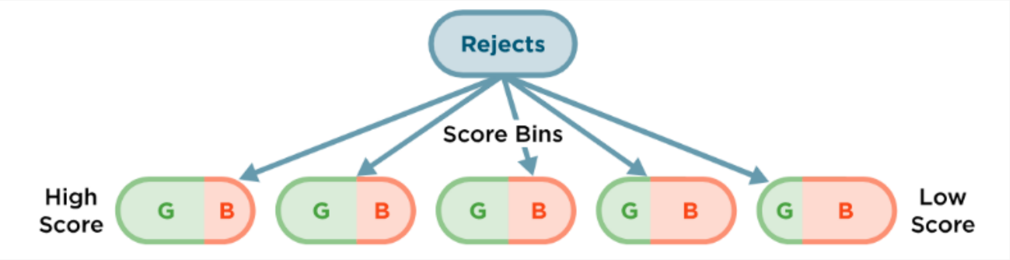
Reject Inference – Approach

Not all rejects are equal especially when it makes up 70% of your population, therefore we will always assign a P(G) and P(B) for each Reject based on Risk Score.



There are two preferred methods of doing this:

1. Building Logistical Regression Models on the past Decision and using these models to Infer.
2. Using a Bureau Model calibrated on internal performance to Infer.

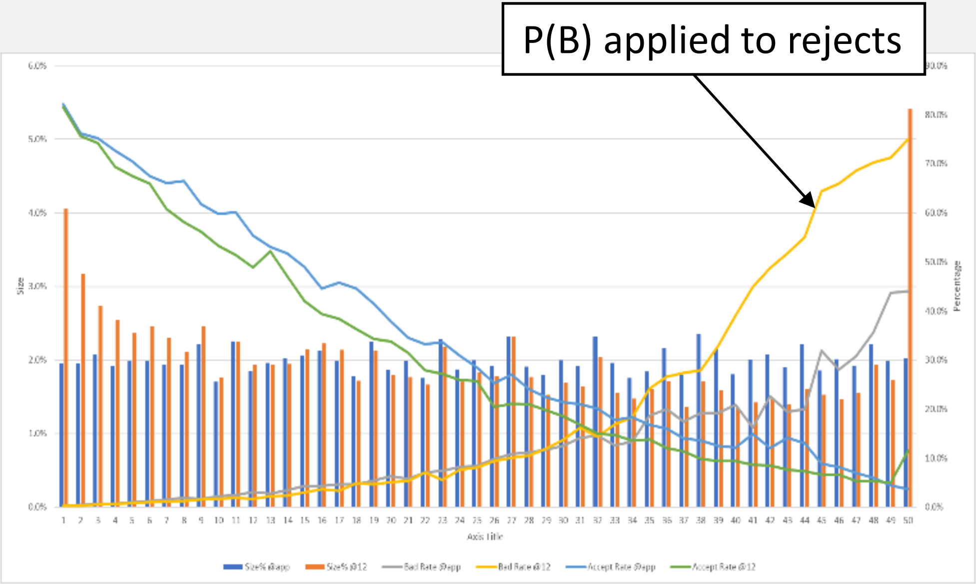
Reject Inference – Approach 1

1. Building a logistical regression model on the Known Good Bad population.
2. Building logistical regression model on the previous Accept Reject decision.
3. The Inferred Probability for each Reject is then assigned based on the following formula: $P(\inf G) = P(KG) \times P(A)^x$

+	−
Can control Influence of Inference using the Power Function	Depends on previous Internal Decision

Reject Inference – Approach 2

1. Apply a Bureau Score on to the Accept population @(Time of Application) and band population into equal bands.
2. Apply the same Bureau Model @(Time of Outcome) and apply same banding.
3. Apply known performance associated with the @(Time of Outcome) of Accepts to the Rejects based on the bureau score for the reject @(Time of Application).



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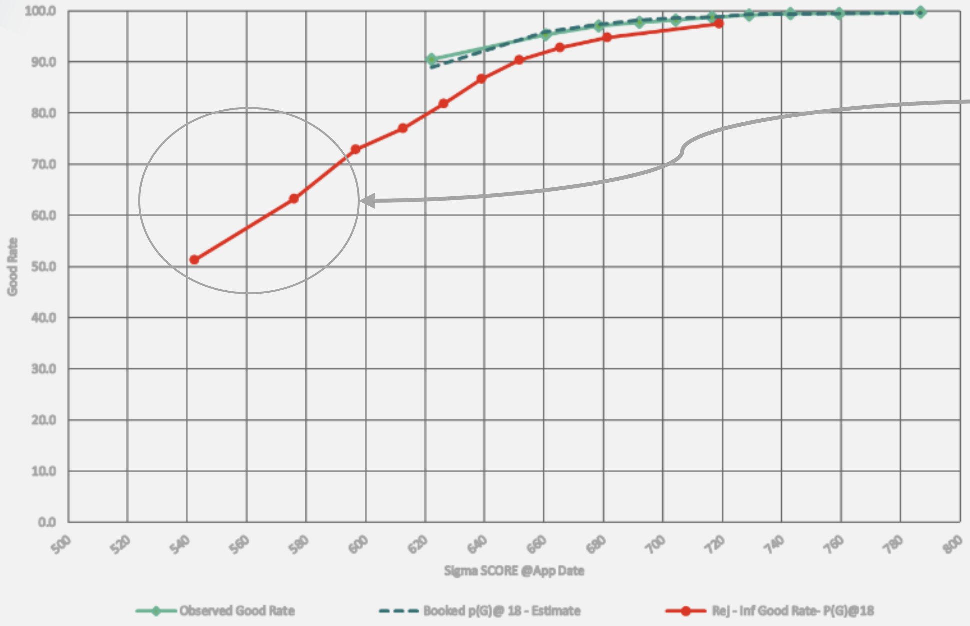
Reject Inference – Approach 2



Inference is heavily influenced by population not likely to result in a swap in.

+	−
External Performance Included	Susceptible to Over-Inferring No lever to adjust influence of Inference

Each point in the Graph represents 10% of the population.

Modeller

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Reject Inference – Solving for Over-Inferring

What is always done:

- The rejects are almost always weighed down, whether over-inferring is an issue or not.
- The reason being when approx. 2/3 of your development population is rejects, you want to limit its influence on the model to ensure your model separation is where you want it to be.
- Weight applied between 30%-50%.

Other options:

- Cut out a portion of rejected – for example worst 20%.
- Apply some form of sampling on the rejects – take all marginal rejects and sample the worst rejects.
- One sizes fits all reject inference doesn't work well for segmented models.

Reject Inference

Other things to consider when you have a High Decline Rate:

- Information collected at the time of the application is susceptible to manipulation - Customers, Agents, Dealers often work out they can influence the Risk Decision based on the information included in the application and use this to their advantage.
- Alternately, if information legitimately changes in the application process in can change the risk decision and pricing of the loan, causing customers dissatisfaction and higher NTU rates (e.g. Loan to Value).
- In a market with more volatility some information is more valuable as a strategic lever and if it’s in the scorecard there is less flexibility to do this (again LTV is a good example).

Section 2

Debt Restructuring

Debt Restructuring

- Debt Restructuring is a common practise aimed at helping non-performing customers.
- What makes restructuring in South Africa unique is the South African National Credit Regulator has created a means by which customers can force Credit Providers to restructure their credit.
- This is done via a 3rd party called a Debt Counsellors at a cost to the customer.

1. Customer engages the services of a Debt Counsellor
2. Debt Counsellors assess the customer's indebtedness
3. Debt Counsellors applies for a court order on behalf of customer if there is sufficient evidence
4. Order is granted and Credit Providers are required to adjust terms based on the Debt Counsellor's stipulations
5. Lenders are not allowed to lend to customers under Debt Counselling

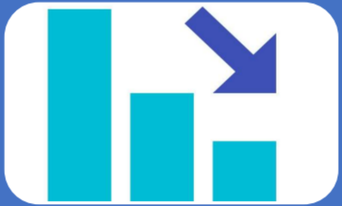
Debt Restructuring

Interesting things to note

- Debt Counsellors are allowed to advertised - the ads often highlight the benefits of their services and not the consequences

Interesting Trends as a Result of 3rd Party Debt Counselling

- Paying customers are sometimes granted Debt Restructuring – customers would have poor payment behaviour on other credit or with other institutions



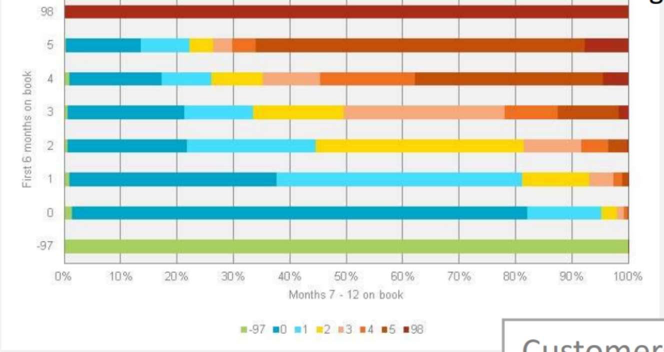
Impact of Debt Restructure on Business

- Negative impact on Profit, especially on unsecured credit, because interest rates are drop significantly, less impact on Profit for secured products because terms are extended and there is less margin to drop interest rate.
- Debt Restructured customers are not good for business.

Debt Restructuring

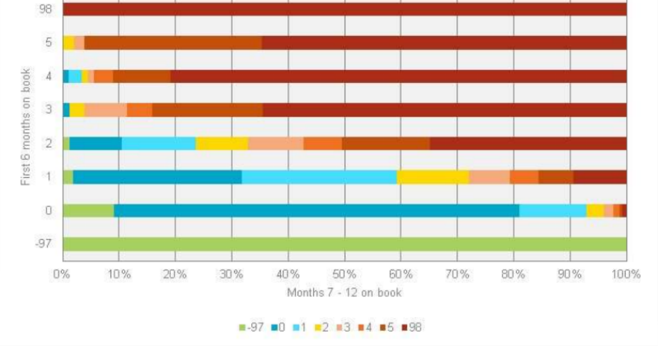
Non Debt Restructured Accounts

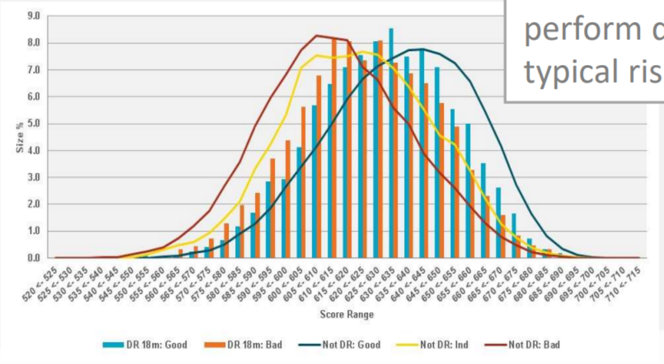
Debt Restructured Accounts after Debt Restructuring



Customers in Debt Counselling perform differently from typical risk behaviour.

Debt Restructured Accounts before Debt Restructuring



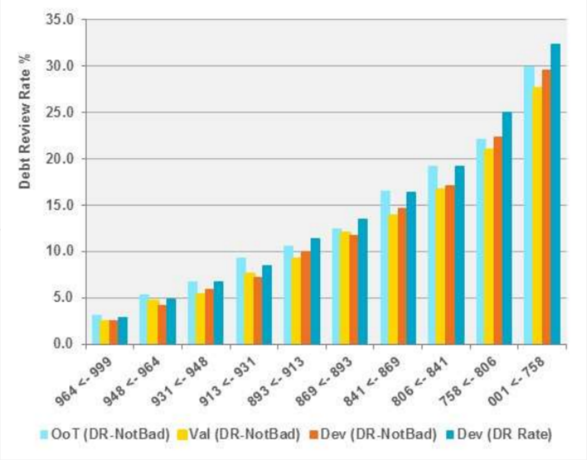


Debt Restructuring – modelling the population

- Targeted the population in Debt Counselling that didn't fit the risk model definition of bad.
- This prevents the development on another Typical Risk Model.
- Creates a model that picks up on customers heading toward over indebtedness and default.
- Ranks well on both non-performing and performing Debt Restructured accounts.

Debt Restructuring

- Utilisation Characteristics
- Increased Number of Loans
- Increase in Unsecured Credit
- Credit across multiple providers
- Recent Trades



✖ Not in Model: Default Variables ✖

Debt Restructuring

- Not highly correlated with Risk.
- Predicts likelihood of all Debt Review customers – Paying and Non Paying
- Ranks customers well based on Affordability

- The model Target is important, the clear it is the stronger your model.

Section 3

Variable Bias

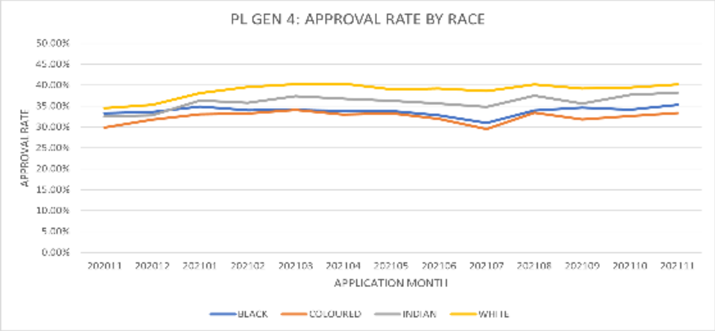
Variables Bias

When there is inequality weighted against certain populations there is always likelihood of variables bias.

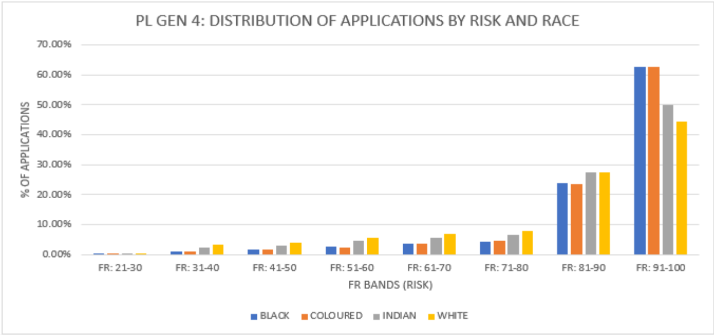
What we do to prevent this:

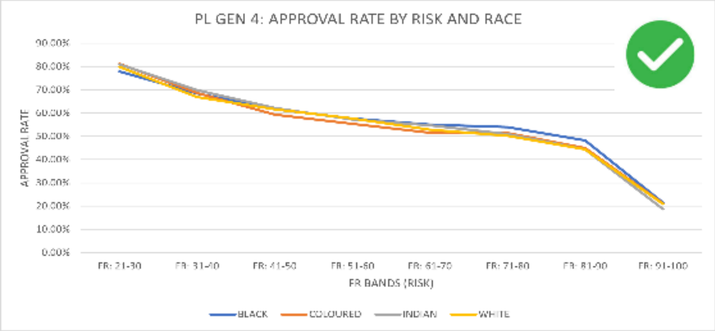
- **Avoid** demographic variables, and not just race and gender – variables like where a customers lives, how many dependents they have, what type of marriage contract or if they are married, all have a tendency to be a proxy for race/gender and drive bias in models.
- **Check All Features in All Scorecards**

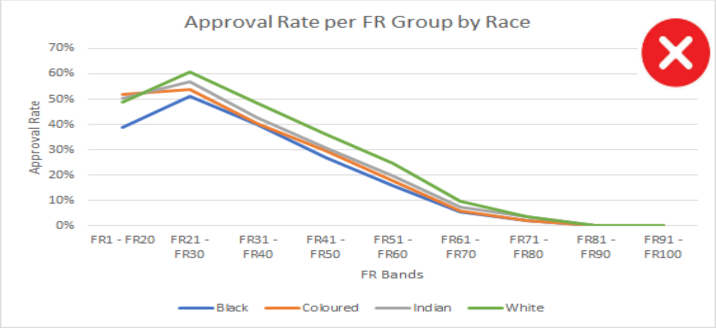
Variables Bias – check 1 , approval rates



Cause

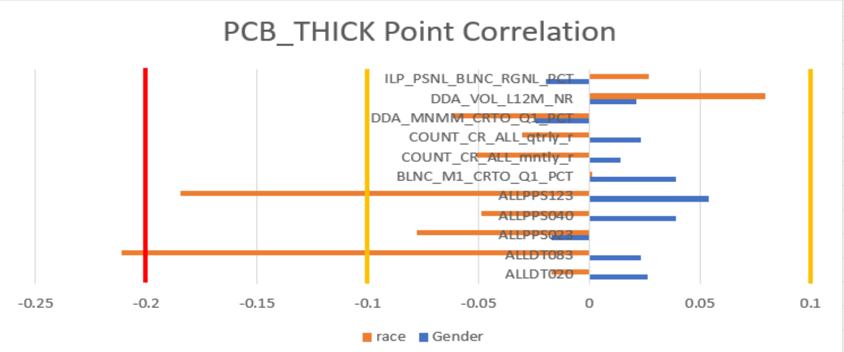


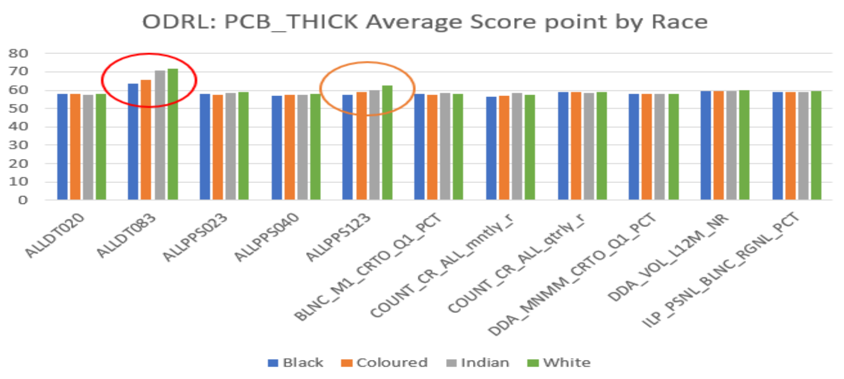




Approval Rates over time will likely show inequality if there is inequality, certain populations might have a high portion of population weighted towards high risk, however it’s important a normalised view doesn’t.

Variables Bias – check 2, correlation/points

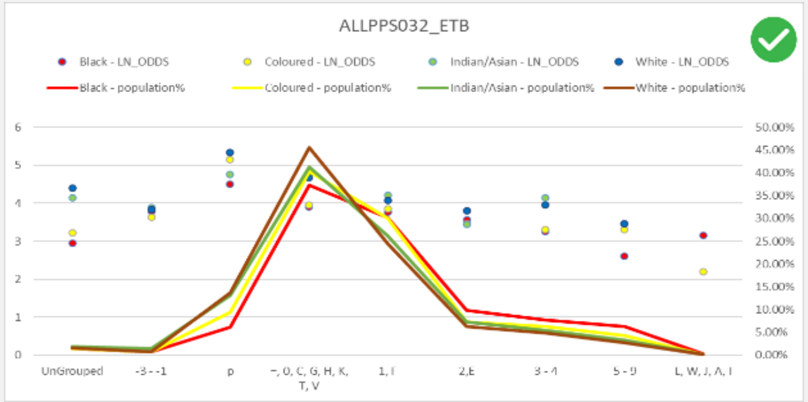




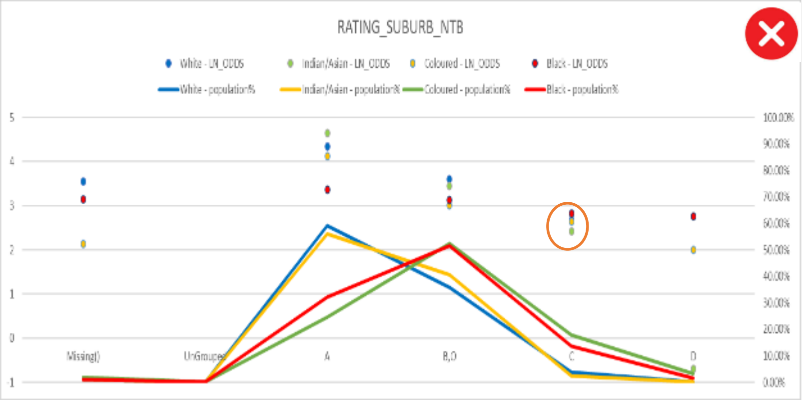
- Individual characteristics are checks for Correlation to Race and Gender.
- The Average Point per characteristic are compared to Race and Gender.
- If there are higher Correlations and/or Average Points differences to Race and/or Gender then the distribution and performance of the characteristics at group level across the different populations are investigated.

Variables Bias – check 3, characteristic check

Below are two characteristics that were either correlated to race and/or had average point discrepancy.



ALLPPS032_ETB shows a correlation with race. When looking at the performance of this characteristic, it shows that the population for all the race categories are similarly distributed between the different buckets.



There is a higher portion of Black and Coloured populations purchasing in B, C and D Areas. Furthermore, the actual performance of Black and Coloured populations is better in these areas compared to White and Indian. This trend is counter the trend across other characteristics and does indicate bias. The characteristics were removed from the model.

Questions