A Property Analysis

A.1 Proof of Lemma 3.3

Proof. We can rewrite $\mathcal{J}$ to

$$\mathcal{J} = \max_{\mathbf{a}_1,\ldots,\mathbf{a}_m \in \mathbb{A}(\mathbf{x})} \left\{ \frac{1}{m}\sum_{i=1}^{m} P(\mathbf{x},\mathbf{a}_i)G(\mathbf{x},\mathbf{a}_i) + \frac{1}{m}\sum_{i=1}^{m} \min_{\lambda_i \geq 0} \lambda_i H(\mathbf{x},\mathbf{a}_i) + \gamma R\left(\{S_{\mathcal{M}}(\mathbf{x},\mathbf{a}_i)\}_{i=1}^{m}\right) \right\}. \tag{11}$$

We derive the fact that, for any i,

$$\min_{\lambda_i \geq 0} \lambda_i R(\mathbf{x},\mathbf{a}_i) = \begin{cases} -\infty & H(\mathbf{x},\mathbf{a}_i) < 0 \\ 0 & \text{otherwise} \end{cases}$$

where $-\infty$ comes from setting $\lambda_i = \infty$ and 0 is obtained by setting $\lambda_{p_i} = 0$. By the linearity of summation, we can further derive

$$\frac{1}{m}\sum_{i=1}^{m} \min_{\lambda_i \geq 0} \lambda_i R(\mathbf{x},\mathbf{a}_i) = \begin{cases} -\infty & \exists i, H(\mathbf{x},\mathbf{a}_i) < 0 \\ 0 & \text{otherwise} \end{cases}.$$

That is, if any constraint for the robustness is unsatisfied, the dual player will minimize the objective towards $-\infty$; however, the primal player cannot optimize towards ∞ given that the limit of the gain function and the diversity are finite. In other words, if the constraints are satisfied, the primal player can freely optimize the objective. Once $H(\mathbf{x},\mathbf{a}_i) \geq 0, \forall \mathbf{a}_i$ are satisfied, the objective becomes

$$\begin{aligned} \tilde{\mathcal{J}} &\coloneqq \max_{\mathbf{a}_1,\ldots,\mathbf{a}_m \in \mathbb{A}^+(\mathbf{x})} \frac{1}{m}\sum_{i=1}^{m} P(\mathbf{x},\mathbf{a}_i)G(\mathbf{x},\mathbf{a}_i) + \gamma R\left(\{S_{\mathcal{M}}(\mathbf{x},\mathbf{a}_i)\}_{i=1}^{m}\right) \\ &\geq \min_{\mathbf{a}_1,\ldots,\mathbf{a}_m \in \mathbb{A}^+(\mathbf{x})} \frac{1}{m}\sum_{i=1}^{m} P(\mathbf{x},\mathbf{a}_i)G(\mathbf{x},\mathbf{a}_i) + \gamma R\left(\{S_{\mathcal{M}}(\mathbf{x},\mathbf{a}_i)\}_{i=1}^{m}\right) \\ &> 0 \end{aligned} \tag{12}$$

as $P(\mathbf{x},\mathbf{a}_i) > 0$ and $G(\mathbf{x},\mathbf{a}_i) \geq 0$ for any $\mathbf{a}_i \in \mathbb{A}^+(\mathbf{x})$; also, $R \geq 0$ holds. We conclude the proof here. $\square$

A.2 A Probabilistic Relaxation of Robustness

Absolute robustness is difficult to guarantee, and common practice is to relax this via a probabilistic approach [15].

Assume there is a distribution over the sample space $\mathbb{B}_s(\mathbf{x},\mathbf{a})$ denoted by $\Pr(\mathbb{B}_s(\mathbf{x},\mathbf{a}))$. We write $\mathbf{x}' \sim \Pr(\mathbb{B}_s(\mathbf{x},\mathbf{a}))$ to indicate that $\mathbf{x}'$ is sampled from the set $\mathbb{B}_s(\mathbf{x},\mathbf{a})$ under the distribution P. Let $\mathbb{E}[h(\mathbf{x}')|\mathbf{x},\mathbf{a}]$ denote the expectation of $\mathbf{x}'$ in this configuration. Hence, we modify Equation (6) to

$$\mathbb{E}[h(\mathbf{x}')|\mathbf{x},\mathbf{a}] > \tilde{\psi}, \tag{13}$$

where $\tilde{\psi}$ is a function that adjusts the base score threshold ψ. It is crucial to have this threshold function in order to consider the variance of scores in the neighbor set. Particularly, we would like most neighbors to remain in a similarly "good" state, with low variance between them.

Moreover, we explicitly impose $h(S_{\mathcal{M}}(\mathbf{x},\mathbf{a})) - \psi > 0$. It places a hard constraint to avoid the case in which the neighbors of the semi-factual are robust, but the "semi-factual" itself has crossed the decision boundary to become a counterfactual. Whilst somewhat unlikely, this situation is theoretically possible, and requires consideration. In this case, H is re-written as H_p, which represents a combination of (i) the probabilistic robustness, and (ii) the absolute robustness for the semi-factual H_a such that:

$$H_p(\mathbf{x},\mathbf{a}) = \mathbb{E}[h(\mathbf{x}')|\mathbf{x},\mathbf{a}] - \tilde{\psi} \qquad H_a(\mathbf{x},\mathbf{a}) = h(S_{\mathcal{M}}(\mathbf{x},\mathbf{a})) - \psi\,. \tag{14a}$$

In practice, H_p is still non-trivial to solve. Monte Carlo (MC) sampling is a common strategy to apply here such that, by sampling a fixed sized batch $\mathbf{B} = \{\mathbf{x}' : \mathbf{x}' \sim \Pr(\mathbb{B}_s(\mathbf{x},\mathbf{a}))\}$,

$$H_p(\mathbf{x},\mathbf{a}) = \mathbb{E}[h(\mathbf{x}')|\mathbf{x},\mathbf{a}] - \tilde{\psi} \approx (1/|\mathbf{B}|)\textstyle\sum_{\mathbf{x}' \in \mathbf{B}} h(\mathbf{x}') - \tilde{\psi}\,. \tag{15}$$

This implies that we substitute an unbiased estimator for the population mean.

B Actionability Constraints

B.1 Non-Causal

Here we define the actionability constraints used in the various domains. It may be assumed that the direction features are allowed to change corresponds with *positive gain*. We use various sized “action sets" to fully test all algorithms in various setups. The German Credit data used 15 actionable features to be closely in line with Mothilal et al. [28] whom allowed all features to be mutable. However, we also used 7 on Lending Club, and 4 on Adult Census/Breast Cancer to test the algorithms in situations with smaller action spaces also for completeness.

We ordered categorical features in a sensible fashion to “direct" semi-factual “even if" thinking, and when we say a categorical feature could decrease/increase, we are referring to this pre-defined order. If you are interested in the exact ordering, please refer to our code which contains all the lists, but here we summarize. In reality however, a user must specify their exact actionability constraints, what we have specified here is designed to be representative what is possible for the “average" individual.

B.1.1 German Credit Dataset

The continuous features used were ‘duration’, ‘amount’, ‘age’, the categorical ones were ‘status’, ’credit_history’, ‘purpose’, ‘savings’, ‘employment_duration’, ‘installment_rate’, ‘personal_status_sex’, ‘other_debtors’, ’present_residence’, ‘property’, ‘other_installment_plans’, ‘housing’, ‘number_credits’, ‘job’, ‘people_liable’, ‘telephone’, ‘foreign_worker’. As actionable features for semi-factual recourse, we considered the following:

- *duration*: We allowed people to increase the duration of their loan.
- *amount*: We allowed people to increase the amount of their loan.
- *status*: We allowed people to move towards having lower status.
- *credit_history*: We allowed people to move towards e.g. having a late payment if their credit history was otherwise good.
- *savings*: This feature was allowed to decrease.
- *employment_duration*: This feature was allowed to decrease in case people wanted to e.g. start a new job.
- *installment_rate*: This feature was allowed to move towards lower payments.
- *other_debtors*: this feature was allowed to add another co-applicant.
- *present_residence*: This feature was allowed to move towards e.g. renting in case the user desired to do so whilst searching for a new house with their loan.
- *property*: this feature was allowed to move towards having no property in case the user desired to sell their house/car etc to help pay for e.g. a downpayment.
- *other_installment_plans*: This feature was allowed to add other installment plans.
- *housing*: this feature was allowed to move towards renting away from e.g. owning.
- *number_credits*: This feature was allowed to increase if the user desired to acquire more credit cards.
- *job*: this feature was allowed to decrease in case the individual desired to get a different, less demanding job within their institution, or indeed quite their job to e.g. start a business.
- *people_liable*: This feature was allowed to move towards more people being liable.

B.1.2 Lending Club

The continuous features used were ‘loan_amnt’, ‘pub_rec_bankruptcies’, ‘annual_inc’, ‘dti’, the categorical ones were ‘emp_length’, ‘term’, ‘grade’, ‘home_ownership’, ‘purpose’. As actionable features for semi-factual recourse, we considered the following:

- *home_ownership*: This feature was allowed to decrease towards e.g. renting.
- *annual_inc*: this feature was allowed to decrease if the person desired to e.g. work less hours.

- *emp_length*: This feature was allowed to decrease in case the individual desired to change careers.
- *dti*: dept to income ratio, this feature was allowed to increase.
- *pub_rec_bankruptcies*: This feature was allowed to increase in case the user decided they wanted to declare bankruptcy to e.g. try and keep some assets.
- *loan_amnt*: this feature was allowed to increase.
- *term*: This feature was allowed to decrease.

B.1.3 Breast Cancer

The continuous features used were none, the categorical ones were 'agegrp', 'density', 'race', 'Hispanic', 'bmi', 'agefirst', 'nrelbc', 'brstproc', 'lastmamm', 'surgmeno', 'hrt'. As actionable features for semi-factual recourse, we considered the following:

- *bmi*: This feature was allowed to move towards less healthy BMI levels in case the patient e.g. has hypothyroidism.
- *brstproc*: this feature was allowed to move towards having had a previous breast proceedure in case the patient would like to do so or was advised.
- *hrt*: This feature was allowed to move towards starting HRT, in case a person may wish to alleviate synthoms of the menopause.
- *agegrp*: this feature was allowed to get older in case the individual would like to take no action confident that it would not lead to cancer in the next few years/decades.

B.2 Causal

In the causal setting, we allowed a user's age to increase a maximum of 5 years to mimic the motivating examples in the paper about a user having a bank loan accepted. In such a situation, the user may want to e.g. work less hours over the next 5 years whilst they repay the loan, and still have it accepted.

Next, we detail the direction features are allowed to change, and what direction corresponds to *positive gain*.

B.2.1 Adult Income Census

We use the features "sex", "age", "native-country", "marital-status", "education-num", "hours-per-week", which are the variables in the causal graph of Nabi & Shpitser [30]. We consider "age" and "hours-per-week" as actionable. We allow "age" to increase a maximum of five years, and "hours-per-week" to decrease.

For positive gain, we considered: Age, marital status, and eduation-num *increasing* corresponding to positive gain, and hours-per-week *decreasing* corresponding to positive gain. A persons sex was seen as neutral gain.

B.2.2 COMPAS

We use the features "age", "race", "sex" and "priors count", which are the variables in the causal graph of Nabi & Shpitser [30]. We consider "age" and "priors count" as actionable. As actionability constraints, we assume that both features are non-negative and can only be increase. Age specifically is only allowed to increase by 5 years for each individual.

For positive gain, we considered: Age and priors count increasing corresponding to positive gain. A persons sex and race was seen as neutral gain.

C Hyperparameter Choices

C.1 Non-Causal

Here we note the values for the hyperparameters used in our demonstrations. All were obtained though pilot grid-searches across each dataset. The hyperparameter choices are summarized in Table 1

Table 1: Hyperparameter Specifications

Data	λ_p	λ_s	γ_d	γ_p
German credit	30	10	1	$1e^{-1}$
Lending Club	30	10	1	$1e^{-1}$
Breast Cancer	10	10	10	$1e^{-1}$

For S-GEN itself, we used the same hyperparameters everywhere outside of the above table. The number of generations spent searching for a solution was 20. The population size was fixed at [12,24,48,72,96,120], for diversity sizes of [1,2,4,6,8,10], respectively. The mutation rate was 0.05. The number of "elite" solutions passed on for each generation was 4. The probability of a crossover happening was 0.5. The number of Monte Carlo trials for each instance was 100. The continuous features were perturbed (in mutation or population initialization) by the output from sampling a standard normal distribution with standard deviation equal to the max actionable feature value, minus the min actionable feature value, multiplied by 0.05.

C.2 Causal

In our causal tests we chose λ as 1.0, and this was gradually decreased by a momentum of η=0.9 each iteration to put more emphasises on the maximization of gain.

D Algorithm Pseudocode

Algorithm 1 S-GEN: Genetic Algorithm to Generate Semi-Factual Recourse with Robustness and Diversity in a Non-Causal Model Agnostic Setting

Require: $\mathbf{x}$ the user feature
Require: $h(\cdot)$ the predictive model
Require: m the expected number of suggestions
Require: n the number of candidates, $n > m$
Ensure: $\mathbf{R}_{SF}$ the set of semi-factual(s)
Sample n candidates $\mathbf{D} \leftarrow \{\mathbf{x}_i \sim \mathbb{X}^*\}_{i=1}^n$
while the stopping criterion is not satisfied **do**
    Obtain the fitness scores $\mathbf{f}$ with respect to $\mathbf{D}$
    Save the fittest $\mathbf{x}^* \in \mathbf{D}$ according to $\mathbf{f}$
    Let $\mathbf{D}$ evolve by *natural selection* according to $\mathbf{f}$, *crossover*, *mutation*, and *elitism* with $\mathbf{x}^*$
end while
Collect the best m unique candidates from $\{\mathbf{x}' \in \mathbf{D} : h(\mathbf{x}') = h(\mathbf{x}) = 1\}$ to $\mathbf{R}_{SF}$, according to the corresponding fitness scores in $\mathbf{f}$
if $|\mathbf{R}_{SF}| < m$ **then**
    Complement $\mathbf{R}_{SF}$ to m elements with $\mathbf{x}'$ randomly drawn from $\mathbf{R}_{SF}$
end if

E Code

For our full code used please see:

https://anonymous.4open.science/r/NeurIPS_2023-9F62/README.md

The ability to reproduce the results is given.

Algorithm 2 S-GEN: Algorithm to Generate Robust & Diverse Causal Semi-Factual Explanations for Differentiable Classifiers

Require: $\mathbf{x}$ the user feature vector
Require: $h(\cdot)$ the predictive model
Require: $\mathcal{M}$ the **differentiable** SCM
Require: ϵ the epsilon robustness
Require: η the momentum parameter
Require: τ the learning rate
Require: $\mathrm{Proj}(\cdot)$ a projection that ensures the action is actionable
Ensure: $\mathbf{R}_{SF}$ the set of semi-factual(s)

$\mathbf{R}_{SF} \leftarrow \emptyset$
$i \leftarrow 0$
for $\mathbf{a} \in \mathbb{A}(\mathbf{x})$ **do**
  {Check if the initial aciton $\mathbf{a}$ itself is a valid semif-factual}
  Sample a batch of neighbours from $\mathbb{B}_s(\mathbf{x}, \mathbf{a})$, denoted by $\mathcal{B}$
  if $h(S_{\mathcal{M}}(\mathbf{x}, \mathbf{a})) = 0$ or $h(\mathbf{x}') = 0, \exists \mathbf{x}' \in \mathcal{B}_i$ **then**
    break
  end if
  $\mathbf{a}_i \leftarrow \mathbf{a}$
  while not converged **do**
    Sample a batch of neighbours from $\mathbb{B}_s(\mathbf{x}, \mathbf{a}'_i)$, denoted by $\mathcal{B}_i$
    if $h(S_{\mathcal{M}}(\mathbf{x}, \mathbf{a}'_i)) = 0$ or $h(\mathbf{x}') = 0, \exists \mathbf{x}' \in \mathcal{B}_i$ **then**
      break
    end if
    $\mathbf{a}_i \leftarrow \mathbf{a}'_i$
    $\mathcal{J}_i \leftarrow -\lambda_i \mathcal{L}\left(h(\mathbf{x}'_i), h(\mathbf{x})\right) - \sum_{\mathbf{x}'_i \in \mathcal{B}_i} \frac{\lambda_i}{|\mathcal{B}_i|} \mathcal{L}\left(h(S_{\mathcal{M}}(\mathbf{x}, \mathbf{a}_i)), h(\mathbf{x})\right) + \hat{P}(\mathbf{x}, \mathbf{a}_i)\hat{G}(\mathbf{x}, \mathbf{a}_i)$
    $\mathbf{a}'_i \leftarrow \mathrm{Proj}\left(\mathbf{a}_i + \tau \nabla_{\mathbf{a}_i} \mathcal{J}_i\right)$
    $\lambda_i \leftarrow \eta \lambda_i$
  end while
  $\mathbf{R}_{SF} \leftarrow \mathbf{R}_{SF} \cup \{S_{\mathcal{M}}(\mathbf{x}, \mathbf{a}_i)\}$
  $i \leftarrow i + 1$
  if $i \geq m$ **then**
    break
  end if
end for

F Individual Dataset Results

The results are presented in Figure 4.

G Baselines

G.1 Non-Casual

DiCE Our modification to DiCE, starts by generating a counterfactual(s) for a query. Next, we use the algorithm again, but on the generated counterfactuals(s), to make them generate a second counterfactual, which goes back over the decision boundary. In effect, this generates a semi-factual(s) for a query.

PIECE Second, we use the PIECE framework by Kenny and Keane [21], but apply it to tabular data. Following the authors, we divide the training data into two sets, the first corresponding to those predicted as the original class c, and the second to those predicted as the counterfactual class c', these are again split into the respective features. Hence, if there are 2 classes, with 4 features, there are $2 \times 4 = 8$ sets of data. These sets were then modeled using the best fit found for a Beta distribution on continuous features, and a simple Categorical distribution for categorical features. To generate a semi-factual predicted as c, we take the probability of each feature value in the query using the models of the counterfactual class c', and modify each to be its expected statistical value in c'

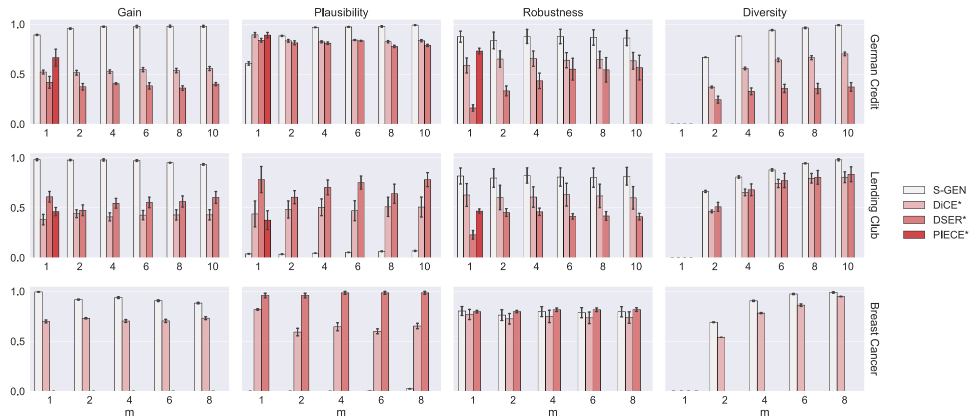

Figure 4: Results: The ability of S-GEN to create semi-factuals is compared to DiCE* and PIECE*. Overall, S-GEN does the best, achieving significantly better results to both baselines on 11/16 tests. Moreover, S-GEN was only significantly worse than either baseline on a single test (i.e., plausibility on German Credit), with the remaining four tests being competitive between methods. Standard error bars are shown.

one-by-one (from the lowest probability to the highest), until the next would take it over the decision boundary. In the case of continuous features, as done by **(author?)** [21], we take the probability as being the minimum of the two integrals either side of the feature value in the distribution. In the case the expected feature values lie outside the actionability range, we clip them to the closest value allowed.

DSER For Diverse Explanation of Reject [1] (DSER) we had to modify the the technique in two main ways. Most notably, the techniques doesn't deal with categorical features, so to overcome this, we optimized treating all one hot encoded features as real-valued, and then projected each categorical feature onto its nearest value. Next, the method addresses diversity by iterating all different sets of possible features, in our domains this is computationally intractable. Hence, we optimize one semi-factual at a time, each time pushing each solution as far as possible from those already found.

G.2 Causal

Karimi et al. (2021) The method by Karimi et al. [19] is a recourse method designed to minimize cost whilst traversing the decision boundary. To modify the technique, we simply stop the optimization when the next step would take it over the decision boundary.

Dominguez et al. (2022) The method by Dominguez et al. [15] is identical to Karimi et al. [19], but they add in a robustness component. Namely, they take an individual x, and solve an inner loss which means that an individual of distance $\epsilon = 0.1$ (in our tests) close to x, with the same recourse given, will also achieve recourse. We simply keep the same optimization process, but aim to solve a different objective. The objective we solve is to move towards the decision boundary, but when the recourse option causes either x or the individual close to it to cross the decision boundary, we terminate the optimization one step prior to this.

H Computational Costs

All tests were run on a MacBook Pro, Apple M1 Pro, 16 GB. Re-running tests will take less than 1 day.

I User Study

Here we show our entire user study for complete transparency. We used the German Credit dataset, but converted the currency into U.S. dollars since it was given to U.S. citizens to complete.

Intro Brief

Thank you for clicking on this study!

<u>Do no take this study on a mobile phone, the tables and images wont display correctly.</u>

Please don't take this study if you did a similar one recently.

You are free to leave at any time.

The study will take around 8mins.

You will be paid $12 per hour for your efforts.

Thank you for your participation!

Enter ID

Please Enter Your Prolific ID Here

Introduction

Introduction

You are going to be shown **six situations** in which a person either has a loan application **approved**, or **rejected**.

You will then be shown **two** different pieces of information for each situation that a bank clerk *could tell* the person.

You are then asked to rate how ***useful*** each of these are. That is, could the information possibly be useful in any way? Or is it not that useful?

Each situation has 4 "features".

Feature Explanation

Features Used in Decision

The four "features" used to decide if each person has their loan **approved** or **rejected** are:

1: Duration: Over how long the applicant wishes to pay back the loan.

2: Amount: How much are they asking to loan from the bank.

3: Savings: How much money does the applicant have saved.

4: Credit Cards: How many credit cards does the applicant have.

These are the only features the bank clerk uses to make decisions.

Click Next

Now, Please Practice On The Next Question

Sample Question

Example Question

Lucas had his bank loan ***accepted***, his features are:

Duration	12 Months
Amount	$2,000
Savings	$500
Credit Cards	2

The two possible things the bank clerk could tell him are:

Option 1: Even if you want to increase your **Duration** to 14 months, and **Amount** to $3,000, we will still accept your loan application.

Option 2: If your **Savings** were $100, and your **Credit Cards** 5, we would have rejected your loan application.

How ***useful*** is each option?

	Not Useful				Very Useful
Option 1	○	○	○	○	○
Option 2	○	○	○	○	○

Click Next 2

Please only participate in this study if you understand the instructions well

Block 15

Remember, the key question is how ***USEFUL*** is each option

Click Next 3

Click Next To Begin The Study

Question 1

Kate had her bank loan ***accepted***, her features are:

Duration	6 Months
Amount	$932
Savings	Over $1000
Credit Cards	2-3

The two possible things the bank clerk could tell her are:

Option 1: Even if you want to increase your **Amount** to $2,841, and increase your number of **Credit Cards** to 4-5, we will still accept your loan application.

Option 2: If your **Duration** was 44 months, and you had had **Savings** less than $100, we would have rejected your loan application.

How ***useful*** is each option?

	Not Useful				Very Useful
Option 1	○	○	○	○	○
Option 2	○	○	○	○	○

Question 2

Paul had his bank loan ***accepted***, his features are:

Duration	18 Months
Amount	$1,239
Savings	Over $1,000
Credit Cards	1

The two possible things the bank clerk could tell him are:

<u>Option 1:</u> Even if you want to increase your **Duration** to 21 Months, and lower your **Savings** to $500-$1,000, we will still accept your loan application.

<u>Option 2:</u> If you asked for an **Amount** of $15,499 (or more), and had had 6 **Credit Cards**, we would have rejected your loan application.

How ***<u>useful</u>*** is each option?

	Not Useful				Very Useful
Option 1	○	○	○	○	○
Option 2	○	○	○	○	○

Question 3

Xue had her bank loan ***<u>accepted</u>***, her features are:

Duration	9 Months
Amount	$1549
Savings	Over $1,000
Credit Cards	1

The two possible things the bank clerk could tell her are:

<u>Option 1:</u> Even if you want to increase your **Duration** to 25 Months, and increase your **Amount** to $4,620, we will still accept your loan application.

<u>Option 2:</u> If you had had 3 **Credit Cards**, and no **Savings**, we would have rejected your loan application.

How ***useful*** is each option?

	Not Useful				Very Useful
Option 1	○	○	○	○	○
Option 2	○	○	○	○	○

Question 4

Siddarth had his bank loan ***rejected***, his features are:

Duration	48 Months
Amount	$6,143
Savings	None
Credit Cards	2-3

The two possible things the bank clerk could tell him are:

Option 1: Even if you increase your **Savings** to $100, and lower your number of **Credit Cards** to 1, we will still reject your loan application.

Option 2: If you lower your **Duration** to 15 Months, and lower your **Amount** to $4,627, we will accept your loan application.

How ***useful*** is each option?

	Not Useful				Very Useful
Option 1	○	○	○	○	○
Option 2	○	○	○	○	○

Question 5

Camila had her bank loan ***rejected***, her features are:

Duration	60 Months
Amount	$15,653
Savings	None
Credit Cards	2-3

The two possible things the bank clerk could tell her are:

Option 1: Even if you increase your **Duration** to 70 Months, and reduce your number of **Credit Cards** to 1, we will still reject your loan application.

Option 2: If you reduce your **Amount** to $7,296 (or less), and you get $1,000+ **Savings**, we will accept your loan application.

How ***useful*** is each option?

	Not Useful				Very Useful
Option 1	○	○	○	○	○
Option 2	○	○	○	○	○

Question 6

Angelo had his bank loan ***rejected***, his features are:

Duration	60 Months
Amount	$7,408
Savings	Less than $100
Credit Cards	2

The two possible things the bank clerk could tell him are:

Option 1: Even if you decrease your **Amount** to $6,505, and increase your **Savings** to over $1000, we will still reject your loan application.

Option 2: If you lower your **Duration** to 5 Months, and you reduce your number of **Credit Cards** to 1, we will accept your loan application.

How ***useful*** is each option?

	Not Useful				Very Useful
Option 1	○	○	○	○	○
Option 2	○	○	○	○	○

Debrief

Debrief: You Have Reached The End

Thank you for your participation, this study was designed to evaluate what kind of explanation people prefer from an artificial intelligence system.