Developing and Experimenting on Approaches to Explainability in AI Systems

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Abstract: There has been a sharp rise in research activities on explainable artificial intelligence (XAI), especially in the context of machine learning (ML). However, there has been less progress in developing and implementing XAI techniques in AI-enabled environments involving non-expert stakeholders. This paper reports our investigations into providing explanations on the outcomes of ML algorithms to non-experts. We investigate the use of three explanation approaches (global, local, and counterfactual), considering decision trees as a use case ML model. We demonstrate the approaches with a sample dataset, and provide empirical results from a study involving over 200 participants. Our results show that most participants have a good understanding of the generated explanations.

1 INTRODUCTION

Overview: Artificial intelligence (AI) technology is increasingly important in many sectors (Russell and Norvig, 2020). At the same time, there is an emerging demand for transparency in deployed AI systems, including via explanations of AI decisions (Goodman and Flaxman, 2017). There is no standard or generally accepted definition of explainable artificial intelligence (XAI), despite the dramatic increase in research interest around the topic (Lipton, 2018). Broadly speaking, XAI can be understood as comprising any process/tool/method that enables stakeholders of AI-enabled systems to comprehend and trust the system.

AI-enabled systems are being developed and deployed in many settings, while AI systems are increasingly expected to operate autonomously (Biran and Cotton, 2017). Machine learning (ML) in particular has been used for a wide range of tasks, and is now pervasive in everyday life. The need for stakeholders to understand and trust the outputs of AI systems (e.g. recommendations or actions) is now a critical issue. Conversely, a lack of transparency and explainabilty is a major barrier to further adoption AI-enabled systems (Gunning and Aha, 2019).

In many cases, recommendations and actions by AI systems can be vital (e.g. in security domains or medical diagnosis). Users not only need to know the output, but also know why that output was given (Tjoa and Guan, 2021). For AI applications where acting on the outputs of an AI system entails high risk, there is a need for proper understanding of the outputs in order to mitigate those risks. If an AI system operates in human-agent environments, it is crucial for explanations to be accepted before actions are taken. For example, if an ML model is used to evaluate CVs for jobs, an administrator needs to know whether a judgement has been influenced by gender or ethnic background (Boehmke and Greenwell, 2019).

In the AI literature *interpretability* and *explainability* are separate but closely related concepts. The former characterises models that are understandable due to inherent characteristics (Gleicher, 2016). The latter characterises interfaces between the outputs of an AI system and its stakeholders. Interpretability can be seen as the ability to provideß meaning in understandable terms to a human, whilst explainability is associated with the notion of explanation as an interface between humans and a decision-maker (Guidotti et al., 2018; Arrieta et al., 2020).

Background on XAI: Historically, explanation methods can be found in the early development of rule-based expert systems and Bayesian networks, such as the work reported by Davis et al. (1977). More recently, there has been a focus on explanations for both white-box and black-box ML models (Lipton, 2018). These can be differentiated into intrinsic and

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post-hoc methods, such as Partial Dependency Plots, LIME, and Shapley (Boehmke and Greenwell, 2019). With these methods explanations are formed around different aspects of a model, such as feature summary statistics, feature summary visualisation, and counterfactual datapoints.

Challenges in XAI: Das and Rad (2020) argue that XAI approaches should be evaluated and selected carefully for different applications. User studies have indicated that typical explanations may not be sufficient to help users make decisions. For example, XAI in critical applications may be impeded by human bias in interpreting visual explanations. Computational complexity and necessary performance optimisations may also harm interpretability of models.

Human-grounded evaluation has made progress recently, and indications are that the XAI landscape is proceeding in a promising prospect (Das and Rad, 2020). Nonetheless, XAI may still benefit from a generally recognised and accepted concept of explainability as well as appropriate evaluation methods. A common foundation would be beneficial to existing and emerging techniques and methods contributed by the community. Such a foundation might provide a unified structure for XAI systems and their evaluation (Arrieta et al., 2020). Since the intended stakeholders of XAI are typically humans, evaluation with humans is important to demonstrate the usefulness of XAI methods and systems. These evaluations may in turn benefit from common evaluation metrics. For example, it was suggested by Arrieta et al. (2020) that a metric or group of metrics might be used to compare the extent to which an XAI model fits the concept of explainability. This is in contrast to the classic metrics (accuracy, F1, sensitivity, etc.) that can describe to what extent a model performs in a definite aspect of explainability (Arrieta et al., 2020).

Contributions: Given these challenges, in this paper we investigate existing XAI tools/platforms that are applicable to both white- and black-box ML models. We investigate and experiment using the XAI tools InterpretML, LIME, and DICE, while considering decision trees as a use case ML model. In particular, we use these tools: (i) to generate global explanations; (ii) to generate local explanations using feature importance; (iii) to generate counterfactual explanations using feature importance when selecting counter datapoints. We also use these tools as part of an explanation prototype that we evaluate in a study involving over 200 participants.

The rest of the paper is organised as follows: in Section 2 we introduce our dataset and XAI tools under consideration, in Section 3 we demonstrate global and local explanations, in Section 4 we demonstrate counterfactual explanations, in Section 5 we present our evaluation, and in Section 6 we conclude.

2 PRELIMINARIES

Dataset: We use a dataset from Kaggle[1] on churn (i.e. attrition) modeling. The dataset includes 14 columns and 10,000 rows. The columns include RowNumber, CustomerId, Surname, CreditScore, Geography, Gender, Age, Tenure, Balance, NumOfProducts, HasCrCard, IsActiveMember, EstimatedSalary, and Exited. The Exited column is the label column with value 1 for stay and 0 for exit.

To build an ML model, we use both Azure Machine Learning Studio[2] and Scikit-learn to generate a decision tree. AzureML Studio can provide visualisations of the dataset and the structure of the decision tree model. Scikit-learn typically generates a more complex decision tree from the same dataset. We use both a simple ML model (a simple tree) and a relatively complex model (a complex tree) in order to investigate implications on explanations. Since we are not concerned with ML itself, we will not detail how to run these tools to generate decision trees, but assume the decision tree has been constructed. For XAI techniques, we start with InterpretML,[3] which offers methods to explain both white-box (i.e. built with an interpretable algorithm) and black-box ML models. LIME and DICE algorithms, PDP and other built-in functions, as well as their extensions are used to generate global, local, and counterfactual explanations.

Examples: Let us take the 1st (customer A) and the 4th (customer D) instances in Figure 1 as examples to illustrate the outcomes of predictions from a decision tree by following tree branches.

CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary
736	0	0	43	4	176134.54	1	1	1	52856.88
685	0	0	40	2	168001.34	2	1	1	167400.29
663	2	1	29	4	102714.65	2	0	0	21170.81
666	1	1	47	5	0	1	0	0	166650.9
741	2	0	36	8	116993.43	2	1	0	168816.22

Figure 1: Example customer instances.

Customer A is aged 43 and has been using only one product from the bank, but has been an active member. In addition, customer A is French (this is where bias might come in when using such algorithm to build the model), thus A is not likely to Churn. The decision path is shown in Figure 2.

[1] https://www.kaggle.com/santoshd3/bank-customers
[2] https://studio.azureml.net/
[3] https://github.com/interpretml/interpret

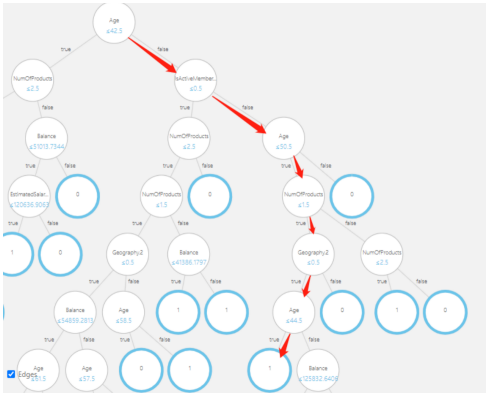


Figure 2: Decision path for customer A.

Customer D is aged 47, has been using only one product, and is not an active member. It is concluded that D is likely to Churn. The decision path is shown in Figure 4.

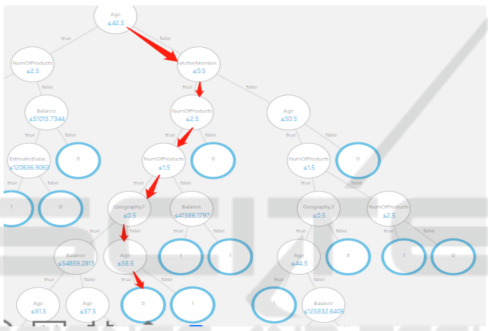


Figure 3: Decision path for customer D.

Explanations: First and foremost, what is an explanation? Miller (2019) states:

> To explain an event is to provide some information about its causal history. In an act of explaining, someone who is in possession of some information about the causal history of some event — explanatory information, I shall call it — tries to convey it to someone else. (Miller, 2019)

This is a definition of explanations from philosophy. When it comes to the relationship between human and AI systems, an AI system plays a role of "someone who is in possession of the explanatory information" and the human is the who that information should be conveyed to. Thus, before providing an explanation, we need to know what information is possessed by an AI system but not by the human.

Contextual Background: A decision tree model usually outputs the importance of features along with a tree model, which can be used to order the sequence of features when selecting which feature to use for explanation. Feature importance finds the most influential features in contributing to the model's overall accuracy or for a particular decision (Boehmke and Greenwell, 2019). One of the difficulties is that a feature may appear multiple times in a tree (or contributing to the split of a tree multiple times). Thus, how to summarise the overall contribution of a feature for a specific instance prediction along a tree path is a challenging problem. One possible solution according to Boehmke and Greenwell (2019) is:

$$\begin{aligned}\hat{f}(x) &= \bar{y} + \sum_{d=1}^{D} \text{split.contrib}\ (d,x) \\ &= \bar{y} + \sum_{j=1}^{p} \text{feat.contrib}\ (j,x)\end{aligned} \tag{1}$$

Equation 1 says that the prediction of instance x, denoted by $\hat{f}(x)$, corresponds to the accumulation of contributions of every feature (feat.contrib(j,x)) from a total of p features that appear on the path for the instance plus the mean of the target outcome ($\bar{y}$).

A feature might be used for more than one split or not at all. We can add the contributions for each of the p features and get an interpretation of how much each feature has contributed to a prediction (Boehmke and Greenwell, 2019). Therefore, an explanation is not simply a traversal of a decision path in a tree but is from the joint consideration of a feature's importance and its accumulated contributions along the path.

Explanation Optimisation: For black-box ML models, some research has sought to simplify models in order to make them more transparent, e.g. by simplifying a neural network model into a decision tree. In this paper, although we take a decision tree model as a use case, but want to investigate and develop explanation approaches that are more generic and applicable to other ML models, including black-box models. We thus investigate post-hoc explanation approaches which can be either model-specific or model-agnostic (Boehmke and Greenwell, 2019). Feature importance and model simplification methods are two broad kinds of model-specific approaches. Model-agnostic approaches include a range of alternative methods, including visual explanations and local explanations (see Figure 4, Boehmke and Greenwell, 2019).

Feature extraction can be applied to both model-agnostic and model-specific approaches, which makes it suitable in the next step of generating model interpretations before moving to the construction of explanations for stakeholders. Explanations based on feature extraction approaches can explain how each feature performs after the model has already been built (which might not be the actual principle of how

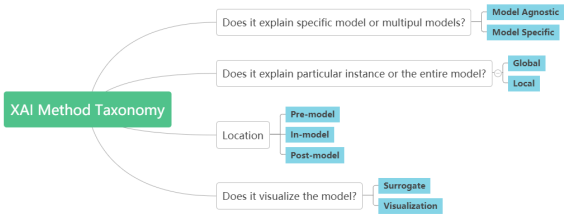


Figure 4: XAI method taxonomy.

the algorithm works inside the original model). Nevertheless, it can give indirect and understandable explanations to stakeholders, and can be further divided into global or local explanations.

3 GLOBAL VS. LOCAL EXPLANATIONS

A global explanation aims to give an overall explanation to a model, whether it is to make a black-box algorithm interpretable or to make a model explainable as a whole, while a local explanation is to provide a tailored explanation to a single specific instance.

3.1 Global Explanation

What is a Good Explanation? Let us take an example from (Hoffman et al., 2018) to illustrate a global explanation which has been assessed as a relatively 'good' explanation:

How do computers predict hurricanes?

- Explanation Judged a priori to be Relatively "Good"
  - Computers have a mathematical model of the atmosphere that divides the world into many small regions, each just a few square kilometres.
  - Each region is defined in terms of its air pressure, temperature, winds, and moisture.
  - The computer calculates what will happen at the boundaries of each region. For example, strong winds in one region will move air into an adjacent region.
  - These calculations must be performed for every boundary between all the regions. This allows the prediction of the path a hurricane will take.
- Explanation Judged a prior to be Relatively "Bad"
  - The computers have a database of all previous hurricanes and the paths that they followed.
  - Once a hurricane is located, using a satellite image, the computer accesses the database and determines the path that was most frequently taken by hurricanes having that initial location.
  - This process is repeated once every hour, tracking the hurricane as it moves.
  - The computers can also tell when the winds and rain will impact the land, and that is when the hurricane warnings are issued.

(Hoffman et al., 2018)

The good explanation seems to have highlighted features much early on ("each region is defined in terms of its air pressure, temperature, winds, and moisture") in contrast to the bad explanation.

Global Analysis: Finding a sequence of features based on their importance is necessary when giving global explanations, which can be achieved by using the built-in functions of a decision tree algorithm, for instance as shown in Figure 5.

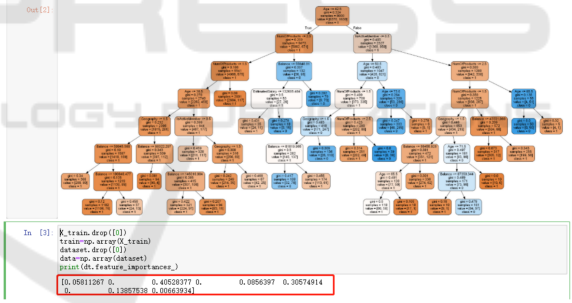


Figure 5: Visualisation of the tree model.

From the plot we can see the importance of each feature: 'Geography' = 0.05, 'Gender' = 0.00, 'Age' = 0.40, 'Tenure' = 0.00, 'Balance' = 0.08, 'NumOfProducts' = 0.30, 'HasCrCard' = 0.00, 'IsActiveMember' = 0.13, 'EstimatedSalary' = 0.00. Then a sequence of features according to their importance could be: 'Age' > 'Number of Products' > 'IsActiveMember' > 'Balance' > Others.

We can also gain relationships between features and a prediction result by using the partial dependence plot (PDP (Friedman, 2001)). Here we take the first and the second important features as an example.

As shown in Figure 6, when other features (values) are unchanged, a customer with the age between 45-75 is more likely to stay instead of churn. Also, if the number of products a customer has is equal to

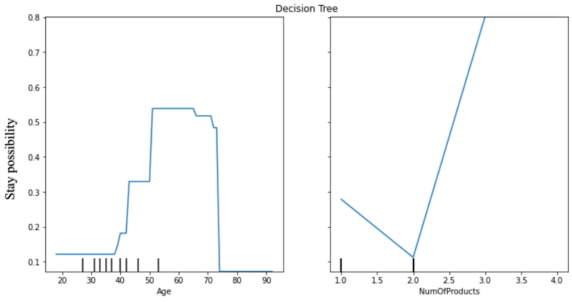


Figure 6: PDP plot of the model.

or more than 2, the customer is more likely to stay. These figures and the conclusions can be used to give both global and local explanations of the model. Accordingly, when giving global explanations, the importance of features are considered first then correlations between the most important features and the outcome can be further taken into account.

3.2 Local Explanation

Local explanation is different from global explanation, it focuses exactly on single predictions. Specifically, local explanation can be further categorised into approximation and example-based approaches (Verma et al., 2020). Approximation approaches sample new datapoints in the vicinity of the datapoint whose prediction from the model needs to be explained, and then fit a linear model (e.g. LIME (Ribeiro et al., 2016)) or extract a rule set from them (e.g. Anchors (Ribeiro et al., 2018), (Verma et al., 2020)). Example-based approaches either select datapoints with the same prediction as that of the explainee's datapoint, or datapoints with the counter-prediction of the explainee datapoint. The latter type of datapoints shall still be close to the explainee datapoint and are termed as "counterfactual" explanations (see the next section).

LIME: LIME is an algorithm that can explain the predictions of any classifier or regressor in a faithful way, by approximating it locally with an interpretable model (Ribeiro et al., 2016). The algorithm can approximate an instance by creating new datapoints around the explainee datapoint to provide a linear model. The model allows us to get an insight of features and how each feature contributes to the prediction of the instance.

The system has given the prediction of this instance as 'not Churn'.

According to Figure 7, the plot at the left is the probabilities of the predictions. The tree-like plot in the middle is the comparative plot of the contributions of each feature. The table on the right represents the

Table 1: An instance of the customer data.

Geography	Gender	Age
2	1	54
Tenure	**NumOfProducts**	**HasCrCard**
3	3	1
IsActiveMember	**EstimatedSalary**	**Balance**
0	96013.5	125889.3

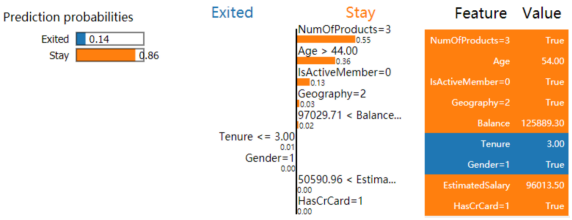


Figure 7: LIME plots.

value of each feature that has been used in sequence by their contributions. In detail, the features in blue mean their contributions to the prediction is negative, whilst the features in orange mean their contributions are positive. In addition, if a trained model is a multi-class classification, the plot of the tree-like part in LIME can be done through a series of similar binary trees, each of which is for one class label as *A or not A*.

Explanations with LIME: LIME is a post-hoc interpretable ML method and thus can be adopted for both white-box and black-box models. The outputs of LIME are the coefficients of features, and these coefficients represent the contributions of features to a prediction. Feature contributions can be used to order features when generating explanations. A sample local explanation might look like:

```
Because the customer's NumOfProducts=2,
secondly, the 32.00 < Age <= 37.00,
thirdly, the Balance <= 0.00 the proba-
bility of the customer to churn is 0.92
```

4 COUNTERFACTUAL EXPLANATION

Global and local explanations we gave are the explanations based on analysing the importance of features or certain properties of the instances themselves. Such explanations are straightforward and exactly reveal how a system has taken features' importance into consideration when ML model. But we also need to consider other factors, which leads us to consider *explanatory relevance*. The idea of explanatory relevance was extended in (Verma et al., 2020) for XAI based on an early work from (Hesslow, 1988): "the effect or the explanandum; i.e., the event to be explained, should be construed, not as an object's hav-

ing a certain property, but as a difference between objects with regard to that property."

There are many examples that have been mentioned in the literature about the importance of counterfactual when giving the explanations. The most classical example is for application of a loan. A customer may want to know the reason why its loan application has been refused by a system, not just as an explanation of what features have been used to derive a conclusion, but also what else can be done to make the result different. In this case, compared to the traditional explanations the counterfactual explanation is more acceptable and cognitively less demanding to both questioner and explainer (Lewis, 1987). (Lipton, 1990) proposes that explanation selection is best described using the Difference Condition: "To explain why P rather than Q, we must cite a causal difference between P and not-Q, consisting of a cause of P and the absence of a corresponding event in the history of not-Q". In (Verma et al., 2020), it was suggested that there is a difference between Lewis's idea, stating that the explanation should be a certain event, and Lipton's explanation which emphasises the difference between the fact and the counter-fact.

Contextual Methods: A recent review paper has concluded the five optimisation objectives of counterfactual explanation, which are *Sparsity, Data Manifold closeness, Causality, Feature-correlation*, and *Outlier risk* (Verma et al., 2020). Another perspective has been mentioned which is *Actionability* (Kanamori et al., 2020). We do not regard actionability as an objective of explanations and thus will omit it from further discussions. So, only the first five qualities will be taken into consideration later when adopting the counterfactual methods.

There are many ways to generate counterfactual explanations. In this paper, we focus on generating explanations with counter-datapoint instead of finding the correlation between different facts. Since we only consider binary classification problems here (e.g. A or not A), defining distances between a counter-datapoint to the explainee-datapoint can be achieved using some known distance measures, such as:

Euclidean: minimise magnitude of each perturbation

Cosine: minimise change in relationship between features

Manhattan: minimise proportion of features that are perturbed

Mahalanobis: minimise magnitude of each perturbation while accounting for correlation between variables

(Lucic et al., 2019)

A counterfactual explanation using counter-datapoint is usually achieved by finding the closest counter-datapoint around the explainee datapoint. However, there might be many different counter-datapoints which have the same minimal distance to the explainee datapoint. When this happens, feature importance and/or user's needs can influence how an explanation can be formed. As pointed by (Wachter et al., 2017): "in many situations, providing several explanations covering a range of diverse counterfactuals corresponding to relevant or informative 'close possible worlds' rather than 'the closest possible world' may be more helpful."

What is more, an ML model itself might not be trustworthy when giving a specific counter-datapoint. In other words, we cannot just use the closest counter-datapoint as the counterfactual datapoint based only on the trained model but ignoring the potential value of the original data. Thus, we need to use the datapoint that is on the data manifold (in other words, the counter-datapoint should follow the trends of datapoints of the original dataset).

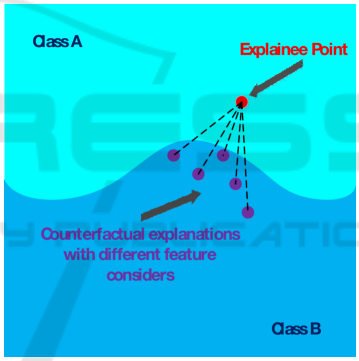


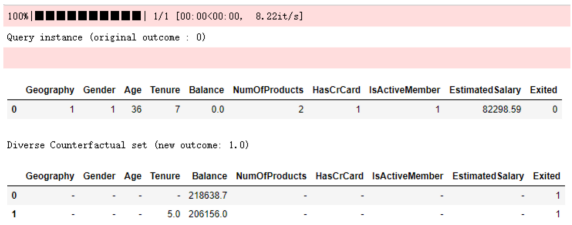
Figure 8: Counterfactual explanation using the closest datapoints.

Implementation: The cosine distance is mostly adopted when the model is built on the purpose of text analysis. Among the other three distance standards, the Euclidean distance is the most direct distance between two points which is used in this paper and it normalises feature value ranges as shown in Equation 2.

$$d\left(x_i, x'\right) = \sum_{k \in F} \frac{\left(x_{i,k} - x'_k\right)^2}{\text{std}_{j \in P}\left(x_{j,k}\right)} \tag{2}$$

Here, 'k" and "F" stand for feature "k" in the feature set "F". "std" stands for the standard deviation. The distance between x_i and x' is equal to the summary of distances between their features divided by the standard deviation of them and this is used in DICE (Mothilal et al., 2020). it can be adopted on both white-box and black-box models, and we use the

DICE package to give counterfactual explanations on the decision tree model in this paper.



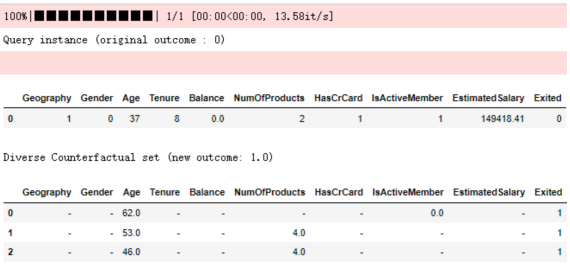
	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	1	1	36	7	0.0	2	1	1	82298.59	0

	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	-	-	-	-	218638.7	-	-	-	-	1
1	-	-	-	5.0	206156.0	-	-	-	-	1

Figure 9: Counterfactual explanations in DICE without feature value restrictions.

Here we use the instance in Figure 9 as an example to give two counterfactual instances. In this figure, the middle row represents the feature values of the explainee datapoint and the bottom rows represent two counter-datapoints. In these two rows, features with "-" mean that these features have the same values as the explainee datapoint. Accordingly, the features with values present are those which are different from the explainee datapoint's features. We can see the original result of prediction is that the customer is likely to churn (note that for the label "Exited", "0" stands for "churn" and "1" stands for "stay"). We found the counter-datapoints that hypothetically saying that, either its balance can increase to £218638.7, or its tenure can decrease to 5 plus his balance can increase to £206156.0, then the customer is not likely to churn. However, neither Tenure nor Balance is a feature with a significant contribution to a prediction in this case. Therefore, we need to consider differences between the most significant features' values when selecting counter datapoints.

Optimisation: In order to give counterfactual explanations with the change of the most important features, we need to refer to the feature importance that we gave in the last section. In (Lewis, 1987), Ramaravind et al tested the correlation between feature importance algorithm LIME and SHAP with the counterfactual methods DICE and WatcherCFfeature, and concluded that "importance induced from DICE and WachterCF can be highly correlated with LIME and SHAP on low-dimensional datasets such as Adult-Income, they become more different as the feature dimension grows (Lewis, 1987)." In this study, the dataset we use as an example has nine features which is much less than that has been mentioned in (Lewis, 1987) where the number of features is more than 200. Accordingly, we modified LIME considering feature importance to constraint how counter-datapoints selection can be optimised. Figure 10 shows counter-datapoints before constrains and Figure 11 shows how optimised counter-datapoints were selected. AS we can see, in Figure 11, the range on Age from counter datapoints is reduced to be closer to that of the explainee datapoint.



	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	1	0	37	8	0.0	2	1	1	149418.41	0

	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	-	-	62.0	-	-	-	-	0.0	-	1
1	-	-	53.0	-	-	4.0	-	-	-	1
2	-	-	46.0	-	-	4.0	-	-	-	1

Figure 10: Counterfactual explanations with few or no constraints on features values.

	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	1	0	37	8	0.0	2	1	1	149418.41	0

Diverse Counterfactual set (new outcome: 1.0)

	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	-	-	49.0	-	-	3.0	-	-	-	1
1	-	-	49.0	-	-	4.0	-	-	-	1
2	-	-	54.0	-	-	-	-	0.0	-	1

Figure 11: Counterfactual explanations with constraints important features.

As such, using the counterfactual datapoint generated, it is possible to further output local explanations with these datapoints as the counterfactual reference as illustated below:

```
Hypothetically, if their Age is 49.0,
and their NumOfProducts is 3.0, they
will be not likely to churn.
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5 EVALUATION

"The property of 'being an explanation' is not a property of statements, it is an interaction" (Kanamori et al., 2020). Accordingly, for most of the time, it can be a suitable evaluation tool to evaluate the explanation by directly asking for feedback from users through delivering questionnaires.

We used an existing evaluation scale *Explanation Satisfaction Scale* which has been used to collecting judgments by research participants feedback after being given the explanations. "The Explanation Satisfaction Scale was based on the literatures in cognitive psychology, philosophy of science, and other pertinent disciplines regarding the features that make explanations good." (Kanamori et al., 2020)

Since the dataset we used is about a banking system, we divided participants into two groups: non-experts and users with banking business experience. An online questionnaire website Wenjuanxing[4] was

[4]https://www.wjx.cn

used to create the questionnaire and the questionnaire was first shared with a groups of participants selected by the first author (with some participants working in Bank of Communications of China), then these initial participants further shared the questionnaire with their colleagues and friends. Eventually, 212 questionnaires were received, 55 of are from banking employees, and 157 are from random non-experts. They are from different provinces and cities within China, and the distribution of the geographical location of participants is shown below.

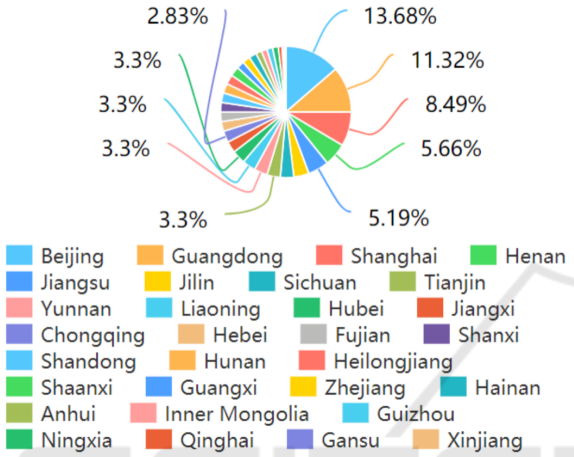

Figure 12: Geographical position distribution of participants.

Evaluation Results: The statistics of the feed-backs are as follow: we have 9 individual questions, the first is a YES/NO question and the rest are with scales from 1 to 5, with 1 the least satisfactory and 5 the most satisfactory of the system to the question posed. These questions are:

1. Are you a practitioner in banking-related industries?
2. Through the output of the system, I can understand how the system works
3. Whether the interpretation of the system output is satisfactory
4. The explanation given by the system is satisfactory in detail
5. The explanation given by the system is relatively complete
6. The explanation given by the system told me how to use it
7. The explanation given by the system satisfies my curiosity and expectations for the system
8. The explanation about the system made me understand the accuracy of the system's judgment
9. The explanation about the system allowed me to know when I can believe it, and on the contrary, it also lets me know when I can't believe it

Among the 212 participants, 74.06% are from non-banking sector. The average of the average score of each question is summarised in Figure 13:

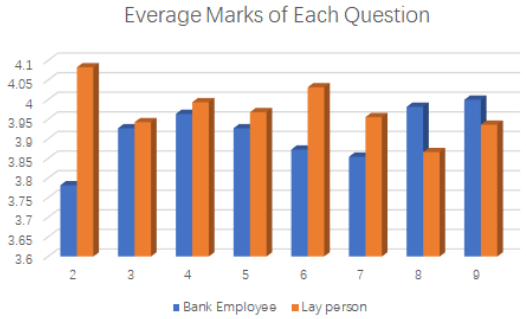

Figure 13: The visualisation represents the average point of each question.

We can see that the average scores of each question both for bank employees and non-experts are all above 3.5, which means the satisfaction degree is overall above average. Interestingly, for the 2nd question, bank employees feel they have less understanding of the system than the non-expert group. For the rest of the questions, the average scores of the remaining questions are not dramatically different. The 4th question stands out as the one which is equally appreciated by both groups. We also calculated the SD and Coefficient of Variation of the scores from each question to see the differences between the scores The result is shown in the table below.

Question / Indicator	2	3	4	5	6	7	8	9
SD	1.126430501	1.165953392	1.171512382	1.218214601	1.128492759	1.124216036	1.144546093	1.119147886
Coefficient of Variation	0.281275932	0.29602649	0.293917899	0.307820614	0.282790148	0.286115005	0.293757593	0.283125718

Figure 14: SD and coefficient of variation of the result.

We can see from the table, the participants' degree of understanding of the explanation varies considerably. Overall, for all of the eight questions, their coefficient variations are higher than 28%. Specifically, the fourth question has the highest SD and coefficient of variation which are 1.22 and 30.78% respectively. Which mean the participants have considerably difference in understanding of *The explanation of how the system works seems complete*. And the seventh question *The explanation of the system shows me how accurate the system is* is of the second highest SD and coefficient of variation. These statistical results confirms the expectation that an explanation has different effects to different group of users.

6 CONCLUSION

In this paper we reported our investigations into XAI. We focused on a decision tree for a sample dataset as a use case to illustrate existing XAI tools/platforms. We discussed and demonstrated how an explanation can be constructed at global and local levels, as well as how such explanations can be further enhanced by using counterfactural datapoints. Finally, we described our evaluation methodology and provided an analysis of participant feedback. Although the work described here is preliminary, we believe it provides some useful starting points for researchers who are new to the field of XAI. Our results show that developing a proper and easily accessible XAI system and interface is a non-trivial task. Deep understanding of the AI system being used, the application domain, and user groups are all important and may have a significant impact on the quality and acceptance of research outcomes. There are several possible avenues for future work:

- Explanation may be more understandable to humans if they incorporate natural language generation (NLG) techniques. When implementing XAI techniques on specific cases, NLG may be used to improve language in final explanations.
- We only considered counterfactual explanations in the context of binary classification models. Additional methods may be adopted to support multi-class classification models.
- We only consider explanations for a single (general) class of stakeholder. However, explanations tailored to other specific classes of stakeholder may be achieved by incorporating preferences or other background information.

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