Benchmark Evaluation of Counterfactual Algorithms for XAI: From a White box to a Black box

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Abstract

Counterfactual explanations have recently been brought to light as a potentially crucial response to obtaining human-understandable explanations from predictive models in Explainable Artificial Intelligence (XAI). This counterfactual explanation claims to be capable of identifying the smallest feature change capable of changing a prediction. It produces an explanation that is more causally informative than factual explanations in terms of expanding human knowledge of decision making. Despite the fact that various counterfactual algorithms have been proposed, the state of the art research still lacks on standardised protocols to evaluate the quality of counterfactual explanations.

In this work, we conducted a benchmark evaluation across different model agnostic counterfactual algorithms in the literature (DiCE, WatcherCF, prototype, unjustifiedCF), and we investigated the counterfactual generation process on different types of machine learning models ranging from a white box (decision tree) to a grey-box (random forest) and a black box (neural network). We evaluated the different counterfactual algorithms using several metrics including proximity, interpretability and functionality for five datasets.

The main findings of this work are the following: (1) without guaranteeing plausibility in the counterfactual generation process, one cannot have meaningful evaluation results. This means that all explainable counterfactual algorithms that do not take into consideration plausibility in their internal mechanisms cannot be evaluated with the current state of the art evaluation metrics; (2) the counterfactual generated are not impacted by the different types of machine learning models; (3) DiCE was the only tested algorithm that was able to generate actionable and plausible counterfactuals, because it provides mechanisms to constraint features; (4) WatcherCF and UnjustifiedCF are limited to continuous variables and can not deal with categorical data.

Keywords: Counterfactual, Explainable artificial intelligence, Decision trees, Random Forests, Deep Neural Networks
1. Introduction

The rapidly growing adoption of Artificial intelligence (AI) has led to the development of deep neural networks for high accuracy of predictions \[1, 2\] in recent years. This advancement has significantly improved the state-of-art in a wide range of fields including computer vision, speech recognition, e-commerce, banking, healthcare, etc \[3\]. Although, advanced machine learning techniques are widely applied in industry, the sophisticated underlying mechanisms of the machine computing systems are opaque and do not provide the user with any understandings of their internal predictive mechanisms. This opaqueness results in several issues including fairness, accountability and transparency, which are in violation of government regulations (e.g., the General Data Protection Regulation (GDPR))\[4, 5\]. The ambiguity in machine learning models (ML) is known as the black box problem. It is hard for a user to understand why a particular prediction was made, consequently generating a lack of trust in the model.

The black box problem has drawn the attention of researchers who are trying to understand why and how an AI system produces a specific outcome or forecast in a research field called Explainable Artificial Intelligence \[6, 7, 8\]. Explainability is a term that refers to the set of methods that allows human users to comprehend and trust the results and output created by machine learning algorithms. Explainable AI is used to describe the expected impact and potential biases for an AI model. It can also help models comply with legal requirements and increase model reliability. A thorough and precise account of how a model generated its outcome is what we refer to as an explanation \[9\].

1.1. Counterfactual in XAI

Recently, counterfactual explanations have been considered as a critical post-hoc method that gives persuasive explanations for users to understand the internal mechanisms of AI models \[10, 11, 12, 13, 14\]. Unlike scoring or raking, which express the (relative) relevance of each feature to the model’s output \[3\], counterfactual explanations are used to show which modifications would be required to get the desired result. This implies that the process of counterfactual generation is resumed to an optimisation problem where the change between the original query and the candidate counterfactual with the desired outcome is the minimum possible. This technique is described as a conditional assertion with a false antecedent and a consequent that depicts how the world would have been if the antecedent had happened (a what-if question) \[15\]. For example, in a scenario where a machine learning algorithm determines whether a person should be granted a loan or not, a counterfactual explanation of why a person was denied a loan may be in the form of a scenario in which you would be awarded a loan if your income was more than 8,000 a year.

1.2. The Problem of Validation of Counterfactual Explanations

Although counterfactuals have been recently explored in the literature, they lack principled approaches and standardised protocols for evaluation. The reason behind this could be that researchers are mainly
focused on creating counterfactuals by utilising different optimisation approaches and heuristic rules in order to find the minimum change that would lead to the desired outcome. These approaches change significantly with different counterfactual models. So there is no consistent way of finding this minimum counterfactual. Although there are some metrics that are used for feature attribution XAI algorithms, such as fidelity [16] and stability [17], there is no standardised way of evaluating XAI algorithms in general, which increases the complexity and difficulty of developing a benchmark evaluation for counterfactuals.

Another important open question in the literature is how different types of machine learning algorithms affect the generation of counterfactuals. Are counterfactuals generated by a deep neural network more difficult to find or harder to interpret given the complexity of the internal mechanisms of the neural network? Or are they easier to interpret given a grey model such as a Random Forrest classifier? Or are they even easier to find in a white box model such as a decision tree?

To the best of our knowledge, the paper that is closely aligned with these research gaps was recently proposed by [18]. In their paper, the authors provide a benchmark for representative counterfactuals in the literature for different evaluation metrics, however the impact of different machine learning models on the counterfactual generation process was not investigated. Additionally, we argue that an evaluation protocol should cover not only quantitative metrics but also the data domain knowledge in a qualitative analysis. For instance, in [19], the authors applied a counterfactual algorithm, DiCE [20], as a means of explanation to predict the next activity in a loan application process. Although DiCE was able to find the minimum counterfactual change, it could not generate counterfactuals that were aligned, meaningful or even interpretable to the loan application process. For this reason, the authors had to propose an extension of DiCE that could take into account the process domain knowledge. This suggests that relying uniquely on quantitative measures does not guarantee the correctness of the generated counterfactual according to the respective domain knowledge.

Given that the formalisation of a counterfactual benchmark evaluation is still in its early stages, to the best of our knowledge, none of the publications looks at the impact of various machine learning algorithms on counterfactual generation. We consequently proposed two assumptions aligned with this circumstance: (1) Is the present counterfactual evaluation sufficient to gauge its quality? (2) Does the choice of machine learning algorithm affect the counterfactual generation process? Answering these two research questions is the aim of this work. To answer it, we (1) Provide a standardised evaluation protocol for assessing counterfactual algorithms, and we (2) Compare the performance of the counterfactual generation process with the different machine learning models by proposed benchmark metrics.

1.3. Contribution

The main contributions of this work are the following:
1. We explore the capability of instance-centric counterfactual explanations: DiCE, Prototype, Unjustified and WatcherCF [21].

2. We investigate the impact of adopting different machine learning models on four selective instance-centric counterfactual algorithms.

3. We propose a benchmark evaluation protocol of the properties of each counterfactual algorithm such as proximity, interpretability and functionality. This benchmark framework implementation assesses different counterfactual generation algorithms. The framework is extendable allowing to easily add new algorithms, and is intended to be a gold standard to evaluate and compare counterfactual generating algorithms. It is open source and the experiments can be found in [https://github.com/LeonChou5311/Counterfactual-benchmark](https://github.com/LeonChou5311/Counterfactual-benchmark).

Our experiments revealed that:

1. The generation of a counterfactual has no significant difference while adopting the white, grey and black-box machine learning model.

2. WatcherCF, Prototype and Unjustified counterfactual algorithms are likely to provide an unrealistic counterfactual with lower explanation dependability. Unjustified counterfactual and WatcherCF could not handle categorical data.

3. DiCE can generate realistic counterfactuals using feature constraints.

4. DiCE performs the best while assessing all properties in our proposed benchmark evaluation.

2. Background

2.1. Model-Agnostic Counterfactual Algorithms

In general, explainable models can be categorized into two main approaches: transparent and opaque models [22][23] as presented in Figure 1. Transparent models are already interpretable by design. They are based on a learning architecture that is already understandable to the decision-maker. These models refer to models like decision trees, logistic regression, and linear regression that are considered interpretable due to their simple structure [23]. Conversely, opaque models are those whose internal mechanics are a mystery because humans are unable to examine how these intelligent systems function. Even if one could look inside these models, their internal mechanisms would be so complex that would be impossible to make sense of their predictions. Model-agnostic models are one of the main approaches that attempt to explain trained machine learning models from a black box prediction.

Explainable machine learning algorithms may be further divided into two categories based on their scope: local and global interpretability. Global interpretability corresponds to the overall set of features that contribute to the predictions of a general predictive system. They also refer to the ability to completely
comprehend the predictive system at once [10]. Alternatively, local interpretability is concerned with generating interpretations for a specific local datapoint rather than providing the overall interpretations of the predictive system. It corresponds to generating interpretations in a specific area of the input space. The decision surface of the model becomes smoother as the input space is restricted. Local interpretability is often achieved through the use of local example-based techniques or local surrogates, which simulate a limited region surrounding an example [24, 25, 23, 26].

In opaque models, explainability may be achieved through a variety of algorithms. Particularly in explanations that rely on attribution [27, 28]. The attribution-based explanation is a local explanation approach that can provide a score or ranking over features, conveying the (relative) importance of each feature to the model’s output [3]. LIME [24] is one of the most representative attribution-based explainable algorithm in the literature that consists of approximating the local decision boundary to a data point. More specifically, LIME perturbs a sample around the input vector in the vicinity of a local decision boundary [29]. Each feature has a weight assigned to it based on a similarity function that compares the distances between the original instance prediction and the sampled locations in the decision boundary’s predictions [24].
Another important feature-attribution algorithm is SHAP that distributes the values of the features in a game theoretic approach. SHAP estimates Shapley values from coalitional game theory to properly share the gain among players in such a way that the contributions of players are fair [30].

2.2. Why Counterfactuals?

Unlike attribute-based algorithms that assign a significance score to each input feature, counterfactual provides instances which produce a different model result with minimal changes in the input features [3]. This mechanism has acquired a lot of attention in recent research and has been determined to have the potential to assist individuals to gain causal understanding by its explanation intuitively [31]. Counterfactuals are seen as a fundamental way to achieving responsibility and accountability [32, 33, 34, 10]. Additionally, Miller, announced that explanations need to be counterfactuals (“contrary-to-fact”) because they allow mental representations of both actual events and alternate events [10]. From another perspective, this approach has also been highlighted by Watcher [13] as a type of explanation that can satisfy GDPR’s policy requirements for explainability. Some other works emphasize the importance of counterfactual thinking in social scenarios. For instance, Pereira and Santos [25], used counterfactuals to understand how individuals that used counterfactual reasoning could improve cooperation in populations. They used evolutionary game theory in their models and they found that a small presence of individuals using counterfactual thinking was enough to nudge an entire population towards highly cooperative standards. In Pereira and Barata [36], the authors argue that counterfactuals are important ingredients to build machines with effective moral capacity. Additionally, In Holzinger et al. [31], the authors also argue that counterfactual thinking is a key ingredient to generate human understandable explanations.

3. Counterfactuals in XAI

3.1. Generation of Counterfactuals

Counterfactual instances can be found by iterative perturbing the input features of the test instance until the desired prediction is obtained [37]. It measures the smallest distance (or change) between a data instance and a counterfactual instance. This notion is described in Equation 1, where \(d(\cdot, \cdot)\) is a measurement for determining the smallest distance between a data point \(x\) and the counterfactual \(x'\).

\[
\arg\min_{x'} d(x, x')
\]

Among all distance measurements, \(L_1\)-norm, depicted in Figure 2 (also known as Manhattan distance), is the most explored distance function in the literature of counterfactuals in XAI [20, 38, 39, 40]. The work described in [13] was the first research that proposed to use this distance function and to perturb the feature of synthetic CF (counterfactual) instances under a loss function balancing closeness to the test instance.
against proximity to the decision border of the counterfactual class. That is to say, the average change in the distance between the initial instance \( x \) and the prediction candidate \( x' \) is limited to this strategy. It applies the same penalty to all parameters, resulting in solutions with larger residuals.

The \( L_2 \)-norm does not yield sparse solutions. It simply calculates the shortest distance between two points and, unlike the \( L_1 \)-norm, can detect a considerably higher inaccuracy, making it more sensitive to outliers. \( L_0 \)-norm is the number of nonzero elements in a vector, and it is used to tally how many features that change between the initial instance \( x \) and the counterfactual candidate \( x' \), resulting in sparse counterfactual candidates. In figure 2, \( L_0 \)-norm is fully undifferentiated, making it difficult to discover strategies to minimize it.

Karimi et al. [41] are the first to investigate the \( L_\infty \)-norm in the setting of counterfactuals in XAI. It is used to limit the maximum change across features between the initial instance \( x \) and the counterfactual candidate \( x' \), the maximum change characteristics. We penalise the cost of the greatest feature by reducing the \( L_\infty \)-norm, which leads to less sparse solutions when compared to other norms.

Figure 2: Graphical visualisation of different \( L_p \)-norms: \( L_0 \)-norms (which is not a norm by definition), the \( L_1 \)-norm (also known as Manhattan distance), the \( L_2 \)-norm (known as the Euclidean distance, and the \( L_\infty \)-norm.

3.2. Properties of counterfactual

Literature suggests a set of properties that need to be satisfied in order to generate a good (interpretable) counterfactual [42][43]. These properties are discussed below.

**Proximity** calculates the distance of a counterfactual from the input data point while generating a counterfactual explanation [44]. Many different distance functions can be employed to measure proximity, resulting in counterfactual candidates with varied features as indicated in Section 5.1. Others in the literature, such as Nearest Neighbour Search [42] or cosine similarity [45], investigate different forms of closeness measures.

**Plausibility** is analogous to *Actionability* and *Reasonability*, which are discussed in [42][44][46][47][48]. It highlights the importance of the generated counterfactuals being valid, as well as the search process ensuring logically plausible outcomes. This implies that a good counterfactual should never alter immutable
features like gender or race. When explaining a counterfactual, explanations like "if you were a man, you would be granted a loan" would show an inherent bias in the explanation. To find good counterfactuals, mutable attributes like income should be altered instead [49].

**Sparsity** is related to the methods used to efficiently find the minimum features that need to be changed to obtain a counterfactual [42]. Counterfactuals should be sparse, with a few changes in their features as possible. The authors of [20] explain that sparsity refers to how many features a user must change in order to switch to the counterfactual class. [44], on the other hand, argues that sparsity is a trade-off between the number of features and the total amount of change required to reach the counterfactual. According to [13], pursuing the “closest feasible world,” or the lowest (minimum-sized) alteration to the world that can be made to achieve a desirable result.

**Diversity** was first mentioned in [38] and further investigated in [20, 50]. Using a distance function to find the nearest points of an instance $x$ can result in extremely similar counterfactual alternatives with minor changes. The approach generates a series of diverse counterfactual explanations for the same data instance $x$ which introduced by [20].

**Feasibility** was developed in response to the criticism that finding the closest alternative to a data instance does not always result in a viable change in the features [47]. Different counterfactual candidates can be seen in Figure 3 where $\alpha$ is the closest counterfactual to the data instance $x$. This position, however, is within the decision boundary. As a result, the black box is unsure about its class, which may lead to skewed counterfactual explanations. To address this problem, [47] argues that counterfactual $\Psi$ is a better one because it falls in a well-defined region of the decision boundary and also corresponds to the point that has the shortest path to $x$. This way, it is possible to generate human-interpretable counterfactuals with the least possible feature changes.

From the definitions of plausibility and feasibility, one can deduce that they are related: a counterfactual must first be plausible before it can be feasible. Plausibility is a property that ensures the legitimacy of generated counterfactuals. This implies that a valid counterfactual should never alter immutable features like gender or race. Feasibility, on the other hand, is concerned with the search for a counterfactual that does not result in a “paradoxical interpretation.”

Low-skilled rejected mortgage applicants may be told to double their wage, according to [47]. This indicates that they must first improve their skill level, which could lead to counterfactual explanations that are both impracticable and so unfeasible. As a result, meeting feasibility ensures plausible counterfactuals, increasing the interpretability of counterfactual explanations.
Figure 3: The different counterfactual candidates for a data instance $x$. According to [13], counterfactual $\alpha$ is the best candidate because it has the shortest Euclidean distance to $x$. Other researchers believe that counterfactual instance $\Psi$ is the best option because it gives a feasible path from $x$ to $\Psi$ [47]. Counterfactual $\beta$ is another candidate of poor quality because it lies in a less defined region of the decision boundary.

4. Counterfactual Approaches in XAI

In their prior work, [21] showed that many counterfactual algorithms shared similar theoretical backgrounds. In total, they analysed 23 model-independent counterfactual techniques for XAI and categorized them into seven groups, each reflecting the “master theoretical algorithm” from which each algorithm was derived. These categories are (1) instance-centric approaches, (2) constraint-centric approaches, (3) genetic centric approaches, (4) regression-centric approaches, (5) game theory-centric Approaches, (6) Case-Based Reasoning Approaches, and (7) Probabilistic-Centric approaches.

- **Instance-Centric.** This approach grounded the theory and counterfactual formalism from [13] [37]. It uses random feature permutations to find counterfactuals that are close to the original instance using a distance function. It mainly consists in finding the minimum distance between a query and the candidate counterfactual. To find counterfactuals, instance-centric algorithms search for innovative loss functions and optimization methods. As a result, they’re more likely to fail the plausibility, feasibility and diversity. However, certain instance-centric algorithms have techniques built into their loss functions to address these difficulties. In particular, FACE and DiCE include procedures in their loss functions to account for the feasibility and variety of their creation. However, the rest of the algorithms, on the other hand, are more likely to fail the feasibility and diversity tests.

- **Constraint-Centric.** Algorithms in this category, such as satisfiability modulo theory solvers, use
various ways to handle the constraint satisfaction problem. The main benefit of these methods is that they are generic and may readily satisfy several counterfactual qualities like feasibility, diversity, and plausibility.

- **Genetic-Centric.** All approaches that use genetic algorithms as an optimisation tool to find counterfactuals fall under this category. Due to its capacity of feature vectors to crossover and mutate in genetic search, these methods frequently satisfy properties including proximity and diversity.

- **Regression-Centric.** This approach uses the weights of a regression model to produce explanations. These methods are remarkably similar to LIME. The idea is that after permuting the features, an interpretable model (in this example, linear regression) fits the newly created data, and the weights of each feature provide explanations. Several properties of counterfactuals based on these methodologies, such as plausibility and diversity, are difficult to meet.

- **Game Theory Centric.** This category encompasses the approaches that use Shapley values to construct explanations. These methods are nearly identical to SHAP. Algorithms that come under this category generally expand the SHAP algorithm to take counterfactuals into account.

- **Case-Based Reasoning (CBR).** These approaches are influenced by the artificial intelligence and cognitive science case-based reasoning paradigm, which portrays the reasoning process as essentially memory-based. These methods frequently handle new problems by retrieving previously stored cases detailing comparable problem-solving episodes and customising their solutions to meet new requirements.

  CBR counterfactual search technique obtains the nearest counterfactuals to a given query from its database. These approaches can easily satisfy different counterfactual properties such as diversity, plausibility and feasibility.

- **Probabilistic-Centric.** The counterfactual generation problem is modelled as a probabilistic problem in this category. Random walks, Markov sampling, variational autoencoders and probabilistic graphical models are frequently used in these approaches to learn efficient data codings in an unsupervised way (PGMs). PGM-based approaches may be able to meet the causality framework suggested by [51].
5. Instance-Centric Counterfactual Algorithms

In this study, we evaluate the performance of several machine learning models using instance-centric approaches. We focus on this approach because of its popularity and simplicity. Most importantly, we consider that instance-centric approaches constitute the basis of the majority of counterfactual algorithms in the literature.

The following sections present a full description of each of the instance-centric counterfactual algorithms proposed in the literature.

5.1. WatcherCF

WatcherCF [13] corresponds to one of the first algorithms in model-agnostic counterfactuals for XAI. They extend the notion of a minimum distance between datapoints that was proposed initially by [37]. The goal is to find a counterfactual \(x'\) as close as possible to the original point \(x_i\) such that a new target \(y'\) (the counterfactual) is found.

**Loss function**

The loss function takes as input the data instance to be explained, \(x\), the counterfactual candidate, \(x'\), and a parameter \(\lambda\), that balances the distance in the prediction (first term) against the distance in feature values (second term) [49]. The higher the value of \(\lambda\), the closer the counterfactual candidate, \(x'\), is to the desired outcome, \(y'\). Equation 2 presents the loss function and respective optimization problem proposed by [13]. The authors argue that the type of optimiser is relatively unimportant since most optimisers used to train classifiers work in this approach.

\[
L(x, x', y', \lambda) = \lambda (f(x') - y')^2 + d(x, x')
\]

\[
\arg\min_{x'} \max_{\lambda} L(x, x', y', \lambda)
\]

**Distance function**

Although the choice of optimiser does not impact the search for counterfactuals, the choice of the distance function does. [13] argue that the \(L_1\)-norm normalized by the inverse of the median absolute deviation of feature \(j\) over the dataset is one of the best performing distance functions because it ensures the sparsity of
the counterfactual candidates. Equation 3 presents the distance function used in their loss function.

\[ d(x, x') = \sum_{j=1}^{p} \frac{|x_j - x'_j|}{MAD_j} \]

where

\[ MAD_j = \text{median}_{i \in \{1, \ldots, n\}} |x_{i,j} - \text{median}_{l \in \{1, \ldots, n\}} (x_{l,j})| \]

Optimization algorithm: The Adam Gradient descent algorithm is used to minimize Equation 2.

5.2. Prototype Counterfactuals

The Prototype Guided Explanations method [52] consists of adding a prototype loss term in the objective result to generate more interpretable counterfactuals. The authors performed experiments with two types of prototypes: an encoder or k-d trees, which resulted in a significant speed-up in the counterfactual search ad generation process.

Loss function

The loss function consists in two different steps: (1) to guide the perturbations \( \delta \) towards an interpretable counterfactual \( x_{cf} \) which falls in the distribution of counterfactual class \( i \), and (2) to accelerate the counterfactual searching process. This is achieved through Equation 4.

\[ \text{Loss} = c \cdot L_{\text{pred}} + \beta \cdot L_1 + L_2 + L_{AE} + L_{\text{proto}}. \] (4)

The \( L_{\text{pred}} \) measures the divergence between the class prediction probabilities, \( L_1 \) and \( L_2 \) correspond to the elastic net regularizer, \( L_{AE} \) represents an autoencoder loss term that penalizes out-of-distribution counterfactual candidate instances (which can lead to uninterpretable counterfactuals). Finally, \( L_{\text{proto}} \) is used to speed up the search process by guiding the counterfactual candidate instances towards an interpretable solution.

Distance function

[52] use the \( L_2 \)-norm to find the closest encoding of perturbed instances, \( ENC(x + \delta) \) of a data instance, \( x \), to its prototype class, \( proto_i \). This is given by Equation 5.

\[ L_{\text{proto}} = \theta \| ENC(x + \delta) - proto_i \|_2^2 \] (5)

Optimization function
adopted a fast integrative threshold algorithm (FISTA) which helps the perturbation parameter \( \delta \) to reach momentum for \( N \) optimization steps. The \( L_1 \) regularization has been used in the optimization function.

### 5.3. Weighted Counterfactuals

Weighted Counterfactuals [39] extend WatcherCF approach in two dimensions by proposing: (1) the concepts of positive and weighted counterfactuals, and (2) two weighting strategies to generate more interpretable counterfactual, one based on global feature importance, the other based on nearest neighbours.

Traditional counterfactuals address the question *why my load was not granted?* through a hypothetical *what-if* scenario. On the other hand, when the desired outcome is reached, positive counterfactuals address the question *how much was I accepted a loan by?*

**Loss function**
The weighted counterfactuals are computed in the same way as the WatcherCF as expressed in Equation 2.

**Distance function**
The distance function used to compute weighted counterfactuals is the same as in WatcherCF, with the addition of a weighting parameter \( \theta_j \),

\[
d(x, x') = \sum_{j=1}^{M} \frac{|x_j - x'_j|}{\text{MAD}_j} \theta_j. \tag{6}
\]

**Optimization algorithm**
While WatcherCF used gradient descent to minimize the loss function, [39] used the Nelder-Mead algorithm, which was initially suggested in the book of [49] and is used to find the minimum of a function in a multidimensional space. The Nelder-Mead algorithm is a better algorithm to deal with the \( L_1 \)-norm since it works well with nonlinear optimization problems for which derivatives may not be known.

Experiments conducted by [39] showed that weights generated from feature importance lead to more compact counterfactuals and consequently offered more human-understandable interpretable features than the ones generated by nearest neighbours.

### 5.4. Feasible and Actionable Counterfactual Explanations (FACE)

FACE [47] aims to build coherent and feasible counterfactuals by using the shortest path distances defined via density-weighted metrics. This approach allows the user to impose additional feasibility and classifier confidence constraints naturally and intuitively. Moreover, FACE uses Dijkstra’s algorithm to find the shortest path between existing training datapoints and the data instance to be explained [44].

Under this approach, feasibility refers to the search of a counterfactual that does not lead to paradoxical interpretations. For instance, low-skilled unsuccessful mortgage applicants may be told to double their salary,
which may be hard without first increasing their skill level. This may render counterfactual explanations that are impractical and sometimes outright offensive [47].

The primary function of FACE’s algorithm is given by Equation 7, where \( f \) corresponds to a positive scalar function and \( \gamma \) is a function that connects the path between a data instance \( x_i \) and a counterfactual candidate instance \( x_j \).

\[
\hat{D}_{f,\gamma} = \sum_i f_p \left( \frac{\gamma(t_{i-1}) + \gamma(t_i)}{2} \right) \| \gamma(t_{i-1}) - \gamma(t_i) \|, \text{where}
\]

\[
\hat{D}_{f,\gamma} = \int_{\gamma} f(\gamma(t)) |\gamma'(t)| \, dt.
\]

When the partition \( \hat{D}_{f,\gamma} \) converges, [47] suggest, for a given threshold \( \epsilon \), using weights of the form

\[
w_{i,j} = f_p \left( \frac{x_i + x_j}{2} \right) \| x_i - x_j \|,
\]

where

\[
\text{when } \| x_i - x_j \| \leq \epsilon.
\]

The \( f \)-distance function is used to quantify the trade-off between the path length and the density in the path. This can subsequently be minimized using Dijkstra’s shortest path algorithm by approximating the \( f \)-distance using a finite graph over the data set.

**Distance Function**

FACE uses the \( L_2 \)-norm in addition to Dijkstra’s algorithm to generate the shortest path between a data instance \( x_i \) and a counterfactual candidate instance \( x_j \).

**Optimization Function**

[47] suggests three approaches that can be used to estimate the weights in Equation 8:

\[
w_{i,j} = f_p \left( \frac{x_i + x_j}{2} \right) \| x_i - x_j \|, \quad w_{i,j} = \tilde{f} \left( \frac{r}{\| x_i + x_j \|} \right) \| x_i - x_j \|, \quad w_{i,j} = \tilde{f} \left( \frac{\epsilon d}{\| x_i + x_j \|} \right) \| x_i - x_j \|
\]

The first equation requires using Kernel Density Estimators to allow convergence, the second requires a \( k \)-NN graph construct, and the third equation requires \( \epsilon \)-graphs. In their experiments, the authors found that the third weight equation together with \( \epsilon \)-graphs generated the most feasible counterfactuals.
5.5. Diverse Counterfactual Explanations (DiCE)

DiCE [20] is an extension and improvement of the WatcherCF [13] throughout different properties: Diversity, proximity, and sparsity. DiCE generates a set of diverse counterfactual explanations for the same data instance \( x \), allowing the user to choose counterfactuals that are more understandable and interpretable. Diversity is formalized as a determinant point process, which is based on the determinant of the matrix containing information about the distances between a counterfactual candidate instance and the data instance to be explained.

**Loss Function**

In DiCE, the loss function, stated in Equation 10, results from a linear combination of three components: (1) a hinge loss function that is a metric that minimizes the distance between the user prediction \( f(\cdot) \) for \( c_i \)'s and an ideal outcome \( y \), \( loss(f(c_i), y) \), (2) a proximity factor, which is given by a distance function, and (3) a diversity factor \( dpp\_diversity(c_1, \ldots, c_k) \).

\[
C(x) = \arg\min_{c_1, \ldots, c_k} \frac{1}{k} \sum_{i=1}^{k} y loss(f(c_i), y) + \frac{\lambda_1}{k} \sum_{i=1}^{k} dist(c_i, x) - \lambda_2 dpp\_diversity(c_1, \ldots, c_k)
\]  

\textbf{(10)}

**Distance Function**

DiCE uses the \( L_1 \)-norm normalized by the inverse of the median absolute deviation of feature \( j \) over the dataset just like in \( b\text{-counterfactual} \) [13].

**Optimization Function**

Gradient descent is used to minimize Equation 10.

5.6. Unjustified Counterfactual Explanations (UnjustifiedCF)

In the context of post-hoc interpretability, [53] addresses the problem of determining the minimal changes to alter a prediction by proposing an inverse classification approach. The authors present the Growing Spheres algorithm, which consists of identifying a close neighbour classified differently through the specification of sparsity constraints that define the notion of \( \text{closeness} \). In a later work, the authors proposed to distinguish between justified and unjustified counterfactual explanations [54, 55]. In this sense, unjustified explanations refer to counterfactuals that result from artifacts learned by an interpretable post-hoc model and do not represent the ground truth data. On the other hand, justified explanations refer to counterfactual explanations according to the ground truth data. The Growing Spheres algorithm, referred
above, falls into the category of unjustified counterfactual explanations.

**Loss Function**
To simplify the process for reaching the closest desirable feature, [53] proposed a formalization for binary classification by finding an observation value \( e \), and then classified it into a different class other than \( x \). For instance, \( f(e) \neq f(x) \), indicates that the observation has been classified into the same class as \( x \), and a desirable feature has been found if it is classified to the other class. For the next step, a function has been defined \( c : X \times X \rightarrow R^+ \) such that \( c(x,e) \) is the cost of moving from observation \( x \) to enemy \( e \).

\[
e^* = \arg\min_{e \in X} [c(x,e) \mid f(e) \neq f(x)] \quad \text{with} \quad c(x,e) = ||x-e||_2 + \gamma ||x-e||_0
\]  

(11)

**Distance Function.**
Equation (11) consists in the minimisation of a cost function under the constraint that the observation \( e \) is classified into the same class as \( x \). This cost function is defined as a weighted linear equation consisting of \( L_2 \)-norm and the \( L_0 \)-norm between the observation \( e \) and the class \( x \). The \( L_2 \)-norm computes the proximity between \( x \) and \( e \), while the \( L_0 \)-norm is used as a weighted average to guarantee that the explanation is human-interpretable.

**Optimization Function**
The authors proposed the *Growing Spheres* algorithm to handle as the optimiser. The algorithm applies a greedy method to find the closest feature in all possible directions until the decision boundary is reached. This means that the \( L_2 \)-norm was successfully minimized. The minimum feature change is also addressed through the minimisation of the \( L_0 \)-norm.

Table I summarizes the features of each instance-centric counterfactual algorithms in terms of several properties. One can see from this table that none of the instance-centric counterfactuals is capable of generating causal counterfactuals in a formal causal framework (such as Pearl’s causal graphs, for instance). One can also see that DiCE is the algorithm that satisfies the majority of the properties, namely it can generate as set of diverse realistic and plausible counterfactuals and at the same time minimize the number of changes in features. This table is the result from the previous survey of Chou et al. [21].
Table 1: Classification of Instance-centric model-agnostic algorithms as proposed by Chou et al. [21].

6. Experiment

6.1. Experiment design

While summarizing the research findings for a systematic literature review in Chou et al. [21] and the several research which evaluates the performance between white, grey and black box models [60, 61, 62], we observed that the performance of the counterfactual algorithm generated from different machine learning algorithms is insufficiently investigated in the literature. This led us to question: How does the choice of different machine learning models impact the results generated by XAI counterfactuals algorithms? In other words, we are interested in understanding if a white box, a grey box or a black box model contribute to the generation of different counterfactuals. Our hypothesis is that since black boxes such as neural networks have a very complex internal structure will difficult the generation of counterfactual explanations when compared to a white box model such as a decision tree.

To address this question, we propose an experimental design (presented in Figure 4) to examine the performance of four instance-centric counterfactual algorithms on three predictive models: a white box (decision tree), a grey box (random forest) and a back box (neural network). In Figure 4, we chose datasets with both numerical and mixed (numerical, categorical) data from the UCI library [1], namely the diabetes, adult, breast cancer, and german datasets (Table 2 presents a description of these datasets). Additionally, we also tested COMPAS [63], since it is a well known dataset in the literature containing racial biases. We preprocessed each dataset by performing a one-hot encoding to the features. The one-hot encoded datasets contained between 8 to 103 features with a total number of observations ranging from 569 to 32561. The data sets were divided into two groups: train (80%) and test (20%), with the training set being used to fit the decision tree, random forest and neural network and the test set being used to produce counterfactuals.

For each counterfactual algorithm, we used 20 instances of the test set (as proposed in Looveren and Klaise [52]) and ran the counterfactual algorithm 5 times on each instance. In the end, we generated 100 counterfactuals from different counterfactual algorithms for each machine learning model.

[1] https://archive.ics.uci.edu/ml/index.php
The counterfactual experiment outcome is recorded based on the category of several assessment metrics such as proximity, interpretability, and functionality. Ideally, a counterfactual should have a minimum value in proximity and the lowest sparsity value (fewer feature changes) as possible. In terms of functionality, an ideal counterfactual algorithm has a high coverage rate and a low-efficiency column value. The stability rate was computed by generating five counterfactuals for each query as suggested in [52]. Section 6.5 provides more information about the different metrics we used.

The selection of the counterfactual algorithm, dataset, machine learning model and evaluation metrics are detailed in the following sections.

6.2. Selection of counterfactual algorithms

We selected instance-centric counterfactual algorithms based on the following requirements: open-source implementation, innovative theoretical and algorithmic techniques, and compatibility (in the code implementation) with the different predictive models used in this benchmark (decision trees, random forests, and neural networks) and compatibility with tabular data. This resulted in four counterfactual algorithms: Prototype [52], WatcherCF [13], DiCE [38] and UnjustifiedCF [53].

These four counterfactual algorithms are distinguished in terms of distance function, loss function, optimisation function and the capability for producing a realistic counterfactual (plausibility). Prototype Guided Explanations, for example, include a prototype loss term (elastic net) in the objective outcome. This algorithm uses either the L$_1$ or L$_2$-norm to find the closest encoding of perturbed instances with a fast integrative threshold algorithm (FISTA) to help the perturbation parameter to reach momentum for $N$ optimization steps [52]. The unjustified counterfactual algorithm is computed in the same way as WatcherCF [13] for loss function with the additional inclusion of a weighting parameter and the L$_0$ norm for distance functions. On the other hand, the L1 norm was mainly recommended for WatcherCF, while DiCE enables the usage of both L$_1$ or L$_2$ norms. In WatcherCF, the author argues that the L$_1$-norm normalized by the inverse of the median absolute deviation (MAD) of feature over the dataset is one of the best and argue that the type of optimiser is relatively unimportant since most optimisers used to train classifiers to work in this approach [13].

DiCE is an extension and improvement of WatcherCF across several properties: diversity, proximity, and sparsity. Diversity is achieved by generating a variety of counterfactual explanations for the same data instance, allowing the user to select more intelligible and interpretable counterfactuals.

Furthermore, the constraint feature differs between counterfactual algorithms. Some algorithms allow for the inclusion of specific constraints to regulate feature modifications, so that immutable features (such as race and gender) do not change. DiCE provides the user with the option of restricting any variable that should be immutable.
Figure 4: Experiment flow chart: The flow chart shows that two categorical and three numerical data from UCI libraries has been conducted into three machine learning models. The outcome of the models will be used for generating a counterfactual (DiCE, Prototype, Unjustified and WatcherCF). The evaluation section displays the metrics to evaluate the result for all counterfactual generations.
Some of these algorithms are limited to continues varies, which provides some challenges in terms of datasets with categorical variables. For instance, WatcherCF and Unjustified counterfactual algorithm cannot deal with categorical features.

6.3. Datasets

The capability for a counterfactual algorithm to process the data is very case sensitive. Therefore, we chose a variety of datasets to broaden the coverage on testing the feature of the selecting instance-centric counterfactual algorithm. For instance, DiCE and Prototype counterfactual algorithms can handle both numerical and categorical data [52, 20]. On the other hand, UnjustifiedCF and WatcherCF are now designed to process numerical data [53, 13].

As a result, we chose five datasets with diverse data types from the public and well-known data repository (UCI Machine Learning Repository [64] ) as follows: (1) Mixed-variable datasets contain categorical and numerical data: Adult income, COMPAS, German credit (2) Numerical data: Brest cancer, Diabetes.

Adult Income [64]. This dataset includes demographic information, level of education, employment, working hours, and other factors. The aim is to determine if an individual’s yearly income surpasses $50,000.

Breast cancer [3]. A digitised image of a fine needle aspirate (FNA) of a breast mass is used to compute features in this dataset. It characterises the properties of the cell nuclei that appear in the photograph and convert it into several parameters. The objective of the dataset is to diagnostically predict whether or not a patient has breast cancer, based on a particular feature value included in the dataset.

COMPAS [4]. The information in this dataset pertains to offenders in Broward County, Florida. The data is looking at the challenge of predicting whether a person would commit a crime again in the next two years.

Diabetes [5]. The diabetes data is consist of several medical parameters and one binary-valued dependent (outcome) parameter. The objective of the dataset is to diagnostically predict whether or not a patient has diabetes, based on particular diagnostic measurements included in the dataset.

German Credit Dataset [6]. This dataset contains records of bank account holders that include personal, financial, and demographic data. Individuals are classified as having good or bad credit risks using the prediction task in this dataset.

Table 2 presents the number of features, the ratio of feature types, the class balance, and the data types (categorical, numerical, and mixed variables).

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2 https://archive.ics.uci.edu/ml/datasets/adult
3 https://archive.ics.uci.edu/ml/datasets/Breast+Cancer+Wisconsin+(Diagnostic)
4 https://github.com/propublica/compas-analysis
5 https://archive.ics.uci.edu/ml/datasets/diabetes
6 https://archive.ics.uci.edu/ml/datasets/statlog+(german+credit+data)
Datasets | Data type | Initial number of instance | Train/test | Original feature number | Features with one-hot-encoding | Number of categorical data | Number of numerical data
--- | --- | --- | --- | --- | --- | --- | ---
Adult-Income | Mixed | 32561 | 26048/6513 | 12 | 103 | 9 | 3
Breast Cancer | Num | 569 | 455/144 | 30 | 30 | NA | 30
COMPAS | Mixed | 7214 | 5773/1441 | 11 | 20 | 5 | 6
Diabetes | Num | 768 | 614/154 | 8 | 8 | NA | 8
German Credit | Mixed | 1000 | 800/200 | 21 | 61 | 14 | 7

Table 2: Data information: The table lists the information for three categorical data (Adult census, COMPAS and German credit) and two numerical data (Breast Cancer and Diabetes). To measure the feature fairly, we applied the one-hot encoding to convert the categorical data to a form that could be provided to the machine learning algorithm for a prediction.

6.4. Machine learning model

In this benchmark, we tested different types of machine learning models in order to have a better understanding of how different predictive models impact the counterfactual generation process.

- **white box model.** According to [61], a white box is a model with clear underlying logic and programming processes, making its decision-making process inherently interpretable. The most popular white box model is simple decision trees, although additional examples include linear regression models, Bayesian networks, and fuzzy cognitive maps [65]. The most straightforward models to describe are linear and monotonic models [60, 62].

- **Grey-box model.** It is a model that combines the capabilities of white box models with black-box models [60], leading to models that are both accurate and interpretable. An example of such model is the random forest which creates an ensemble of trees in order to make a prediction. Although the trees are white box models, the ensemble nature of the model makes it very hard for a human to understand how the prediction were computed [62].

- **Black-box model.** It is a more accurate ML model whose inner workings are so complex that become difficult to understand for a human user. For example, this model would only be aware of the model’s anticipated inputs and outputs. The most popular examples of ML Black-Box models are neural networks [61]. The reason for lower interpretation on the Black-Box models is due to its multi-layer design, which causes the input signal to degrade throughout different non-linear and non-monotonic transformations [60, 62].

We record the accuracy, precision, and recall of each machine learning model in each datasets as table 3.

6.5. Evaluation metrics

Defining the measures to evaluate the explanations and the generating process is an important part of this benchmarking study. However, it is worth noticing that there are no established standardised protocols for evaluating the quality of generated counterfactuals. For this study, we used evaluation metrics from multiple research in [18, 20, 52, 55].

We classified the evaluation metrics into three primary categories: Proximity, interpretability and functionality [38, 18, 55].
| Dataset      | ML algorithm       | Accuracy | Precision | Recall |
|-------------|--------------------|----------|-----------|--------|
| Adult       | Decision tree      | 0.82     | 0.64      | 0.61   |
|             | Random forest      | 0.85     | 0.72      | 0.62   |
|             | Neural network     | 0.85     | 0.69      | 0.68   |
| Breast Cancer | Decision tree     | 0.96     | 0.95      | 0.95   |
|             | Random forest      | 0.99     | 1         | 0.98   |
|             | Neural network     | 0.96     | 1         | 0.9    |
| COMPAS      | Decision tree      | 0.73     | 0.84      | 0.79   |
|             | Random forest      | 0.78     | 0.85      | 0.87   |
|             | Neural network     | 0.8      | 0.83      | 0.92   |
| Diabetes    | Decision tree      | 0.77     | 0.67      | 0.78   |
|             | Random forest      | 0.8      | 0.76      | 0.67   |
|             | Neural network     | 0.77     | 0.78      | 0.53   |
| German credit | Decision tree    | 0.67     | 0.45      | 0.48   |
|             | Random forest      | 0.79     | 0.7       | 0.51   |
|             | Neural network     | 0.77     | 0.63      | 0.59   |

Table 3: The accuracy, precision and recall for each data (Adult, Breast cancer, COMPAS, Diabetes and German credit) with different machine learning models (Decision tree, random forest and neural network) includes decision tree, random forest and neural network models.

- **Proximity.** It is a metric for determining the distance between the initial instance and the generated counterfactual from the instance [38] [20] [55]. It considers the variation of each changed feature. L1 norm is determined as the sum of the vector’s absolute values. The square root of the sum of the squared vector values is used to compute the L2-norm [67]. The mean absolute error distance (MAD) is calculated by dividing the L1 distance between fact and counterfactual by the Median Absolute Deviation (MAD). This metric has been described as a useful metric since it can work with different ranges across features and takes into account the variation of each modified characteristic [20]. The Mahalanobis Distance (MD), commonly used to find multivariate outliers, can take the correlation between features into account [68].

Together, these four distance metrics provide different aspects of the solutions that might be important for specific user defined requirements. For example, if the user is only concerned about having counterfactuals that lie as close as possible to the factual instance, with only continuous features, the Euclidean distance is an important metric to evaluate. However, if the distance is important, but it must be considered different types and ranges of features (such as those found in mixed datasets), the MAD distance can have a higher value. Finally, if the counterfactual should follow correlations between features found in data, the MD distance can be of special importance [18].

- **Interpretability.** It refers to a metric that indicates how interpretable an algorithm is. This category contains several items such as Sparsity rate, Sparsity, Plausibility, Feasibility and Diversity. Sparsity is a frequent measure employed in counterfactual explanation research that counting the number of features that have been twisted while generating a counterfactual [38]. It is desirable to have a short explanation that shows the fewer (minimal) features as possible is ideally. Sparsity rate is the number of the feature changed divided by the number of total features in a dataset. Diversity corresponding to
the capability for a counterfactual algorithm generates several different counterfactual explanations [20, 53, 21, 3]. Feasibility is a statistical similarity of the counterfactual point to the data manifold [47, 53, 3]. Plausibility evaluates the counterfactual algorithm has features to constrain the immutable variable for a generation [69, 18].

- **Functionality.** It is the functional capability of the counterfactual algorithm refers to functionality that contains coverage, compatibility, stability and efficiency. The coverage is proven if the supplied answer flipped the factual class, or in other words, if a counterfactual explanation was discovered [18]. Stability is a metric that assesses an algorithm’s ability to provide consistent results across several runs using the same model and input data [18]. This is determined by comparing the outcomes of two runs with identical settings. High stability indicates that the algorithm delivers similar counterfactual outcomes when given the same input data and model, which is the desired quality for explainable methods. The term “compatibility” refers to determining whether or not an algorithm can handle different forms of data. Efficiency is evaluated by how many seconds for each counterfactual algorithm generate individual instances, this value has been counted as the time for generating a counterfactual per second.

7. Results and Analysis

The evaluation outcome of each instance centric counterfactual algorithm in different dataset groupings (mixed and numerical) are presented in Table 4 and 5. The result has been visualized and analysed based on the category of properties.

- **Evaluation of counterfactual algorithms in terms of proximity:** In Figure 5, DiCE present well than the prototype in both mixed and numerical data for every distance measurement, especially in mixed data. Specially. The closeness case is shown in the german dataset which shows the DiCE generations are 6 times and twice less shortest rate than the prototype in the L_1 and L_2 norm in figure 5. DiCE generate the shortest distance counterfactual is because its loss function is given by a linear combination of three components: (1) A hinge loss function is a metric that minimises the distance between the user prediction; (2) a proximity factor, which is given by a distance function; (3) a diversity factor allows it generates multiple counterfactuals with the shortest distance. However, the prototype adopts a fast integrative threshold algorithm (FISTA) to generate a counterfactual.
| Dataset | ML Model | Counterfactual | L1 | L2 | MAD | MUL | Spa | Spa-rate | Pla | Fea | Div | Cov | Com | Sta | Eff |
|---------|----------|----------------|----|----|-----|-----|-----|---------|-----|-----|-----|-----|-----|-----|-----|
|         | Decision Tree | DICE | 1.78 | 1.14 | 4.38 | 0.31 | 2.28 | 0.19 | | | | 1 | 0 | 0.35 |
|         | Prototype | 12.88 | 3.51 | 2.88 | 1.57 | 14.4 | 1.2 | | | | | 0.25 | 1 | 13.49 |
|         | Random Forest | DICE | 1.71 | 1.13 | 3.42 | 0.31 | 2.13 | 0.18 | | | | 1 | 0 | 0.39 |
|         | Prototype | 12.88 | 3.51 | 2.88 | 1.57 | 14.4 | 1.2 | | | | | 0.25 | 1 | 278.73 |
|         | Neural Network | DICE | 2.05 | 1.27 | 3.84 | 0.39 | 2.38 | 0.2 | | | | 1 | 0 | 0.36 |
|         | Prototype | 12.51 | 3.47 | 2.55 | 1.57 | 14.14 | 1.2 | | | | | 0.35 | 1 | 53.7 |
|        | Decision Tree | DICE | 1.22 | 0.87 | 0.77 | 0.39 | 1.59 | 0.14 | | | | 1 | 0 | 0.08 |
|        | Prototype | 4.7 | 2.08 | 0.72 | 1.21 | 6.5 | 0.59 | | | | | 0.2 | 1 | 13.02 |
|        | Random Forest | DICE | 1.14 | 0.82 | 1.16 | 0.28 | 1.57 | 0.14 | | | | 1 | 0 | 0.13 |
|        | Prototype | 4.85 | 2.11 | 0.72 | 1.21 | 6.67 | 0.61 | | | | | 0.15 | 1 | 107.68 |
|        | Neural Network | DICE | 0.98 | 0.75 | 1.21 | 0.21 | 1.4 | 0.13 | | | | 1 | 0 | 0.09 |
|        | Prototype | 6.13 | 2.45 | 0.7 | 1.43 | 8 | 0.73 | | | | | 0.05 | 1 | 28.47 |

**Table 4: Experiment result for mixed dataset**

| Dataset | ML Model | Counterfactual | L1 | L2 | MAD | MUL | Spa | Spa-rate | Pla | Fea | Div | Cov | Com | Sta | Eff |
|---------|----------|----------------|----|----|-----|-----|-----|---------|-----|-----|-----|-----|-----|-----|-----|
|         | Decision Tree | DICE | 0.94 | 0.68 | 0.36 | 0.1 | 2.24 | 0.07 | | | | 1 | 0 | 0.05 |
|         | Prototype | 0.13 | 0.1 | 0.04 | 0.02 | 29.7 | 0.99 | | | | | 1 | 0 | 0.14 |
|         | WatcherCF | 9.83 | 2.06 | 2.98 | 1.05 | 29.6 | 0.99 | | | | | 0.25 | 1 | 18.22 |
|         | DICE | 24.84 | 4.58 | 8.9 | 2.26 | 30 | 1 | | | | | 0.75 | 1 | 2.49 |
|         | WatcherCF | 24.84 | 4.58 | 8.9 | 2.26 | 30 | 1 | | | | | 0.75 | 1 | 2.49 |
|         | DICE | 3.42 | 1.69 | 0.46 | 0.73 | 3.82 | 0.19 | | | | | 1 | 0 | 0.31 |
|         | Prototype | 20.1 | 4.4 | 1.39 | 2.13 | 22.7 | 1.14 | | | | | 0.5 | 1 | 154.4 |
|         | Neural Network | DICE | 3.93 | 1.83 | 0.43 | 0.77 | 4.33 | 0.22 | | | | 1 | 0 | 0.27 |
|         | Prototype | 20.05 | 4.39 | 1.48 | 2.15 | 22.8 | 1.14 | | | | | 0.5 | 1 | 33.48 |

**Table 5: The experiment result for numerical dataset**
Figure 5: Proximity result: The left section of the graph shows the output of $L_1$, $L_2$, MAD and MD values for DICE and Prototype counterfactual from three machine learning models on three categorical data. Whereas, the right section displays the proximity result for DICE, Proximity, WatcherCF and UnjustifiedCF from three machine learning models on a numerical dataset. It is noticed that the output of the different machine learning models are insignificantly different for each counterfactual factual algorithm in each dataset, especially on the numerical dataset.

Figure 6: Sparsity result: DICE has the lowest number of feature changes than any other counterfactual algorithms in all datasets. Additionally, the generation result demonstrates that the greater the number of input features, the greater the number of features that will be altered. For instance, Adult Income and German credit datasets have more input features than COMPAS.

In the numerical dataset, UnjustifiedCF counterfactual algorithm perform the best among four algorithms, whereas WatcherCF generates the farthest distance than any counterfactual model in the numerical dataset, for example, WatcherCF shows in generates exceeding 26 times proximity rate than Unjustified counterfactual algorithm in breast cancer data for generating the counterfactual in $L_1$-norm. The unjustifiedCF counterfactual algorithm is computed in the same way as [13] for loss function, however, it has the additional inclusion of a weighting parameter which result in better...
Figure 7: Coverage and stability result: The left section of the graph indicates the result of coverage and stability values for DICE and Prototype counterfactual from three machine learning models on three categorical data. On the other hand, the right section of the graph shows the coverage and stability values for DICE, prototype, WacherCF and UnjustifiedCF counterfactual algorithm from three machine learning models on a numerical dataset. This graph shows DiCE have a 100% coverage rate on both categorical and numerical data and the lowest stability rate in the categorical data. Conversely, prototype, WacherCF and the UnjustifiedCF counterfactual algorithm have the 100% stability value.

It is noticed that COMPAS has the lowest proximity value in all datasets due to its fewest number of feature when compared to other datasets.

- Evaluation of counterfactual algorithms in terms of sparsity: DiCE outperform other algorithms by satisfy multiple properties such as plausability, feasibility and diversity in 4 and 5. Besides, DiCE has less feature number change in every machine learning model than other counterfactual algorithms. The sparsity rate ranges from 3 to 10 times less than other algorithms as shown in figure 6. However, Prototype has the highest number of feature changes in the mixed dataset and WatcherCF has the most sparsity rate than the other three algorithms. This generation result is due to the setting of the DiCE for a generation. To generate a realistic counterfactual, I set up the immutable variable such as s gender, race and age for DiCE generation. Consequently, it reduces the number of features to be changed. Figure 6 also indicates that using a different machine learning model to generate a counterfactual algorithm makes no effect. Besides, it is tough to judge the sparsity rate in numerical...
data because there’s no difference in Breast cancer but tiny variances in Diabetes when evaluating prototype, Unjustified counterfactual algorithm, and WatcherCF.

- **Evaluation of counterfactual algorithms in terms of functionality** Overall, DiCE perform well in this category because of the strength on tacking the categorical data, higher performance on time-consuming for a counterfactual generation and 100% coverage rate as shown in Figure 7. Unjustified counterfactual algorithm can successfully generate the counterfactual with 100% return rates for coverage like DiCE. However, it could only provide a counterfactual on numerical data which like WatcherCF.

While assessing the capability of stability, Prototype and WatcherCF have the higher stability which indicates that this algorithm has the same counterfactual return by executing 5 generations for the same query.

Interns of efficiency, DiCE has the lowest generation time in any machine learning model with both mixed and numerical datasets. Whereas, prototype consumes the longest time to generate a counterfactual in both mixed and numerical data. The most extreme scenario is creating a counterfactual in breast cancer, which takes 280 times as long as producing spheres and DiCE in table 4 and table 5.

There are two other observations from these experiments: (1) the different machine learning algorithms do not seem to significantly impact the quality of the counterfactual generated, and (2) if plausibility is not guaranteed, the counterfactual evaluation process will provide meaningless results. This could lead to a generation of unreasonable explanations. The counterfactual was found by changing different features for the input query. For instance, the alteration of the variable such as race, age will lead to the unrealistic result in the COMPAS dataset.

Examples of why it is important to ensure plausibility are the following scenarios: for high-level recidivism criminals to change the level of recidivism from the high class of to lower class, the counterfactual generation suggests that the criminal should change their gender, age, and race to achieve the desired result. Consequently, only if the algorithms have a function that could control the immutable feature a set it unchanged such as DiCE. Then, the generation algorithm can guarantee a reliable output.

8. Conclusion and Future Work

This research proposed a standardise evaluation metric for assessing the quality of a counterfactual generation. This framework was created to investigate how different machine learning models interact with instance-centric counterfactuals.
Our main findings indicate that (1) without guaranteeing plausibility in the counterfactual generation process, one cannot have meaningful evaluation results. This means that all explainable counterfactual algorithms of the literature that do not take into consideration plausibility in their internal mechanisms cannot be evaluated with the current state of the art evaluation metrics, and their reported results may be biased; (2) the counterfactuals generated are not impacted by the different types of machine learning models; (3) DICE outperforms other counterfactual algorithms. This is because of its superior performance in the properties such as proximity, diversity, feasibility, time efficiency and the feature of generating realistic outcomes;

We end the paper alerting that without having counterfactual algorithms that ensure plausibility or without post-hoc methods that can provide plausibility to an existing XAI counterfactual, then the generated counterfactuals can lead to inaccurate reports about their performance and to biased explanations to the users.

In a future perspective, we will investigate a standard evaluation protocol that can ensure that the generated counterfactuals are plausible and that can be validated against a domain knowledge base before being assessed by the current properties.

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