Rule Discovery for Exploratory Causal Reasoning

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Abstract

We study the problem of discovering reliable causal rules from observational data. Traditional descriptive rule discovery techniques do not suffice to this end, as they struggle with the consistent detection of (potentially rare) conditions that have a strong effect on an output variable of interest. Among the sources of inconsistency are that naive empirical effect estimations have a high variance, and, hence, their maximization is highly optimistically biased unless the search is artificially restricted to high frequency events. Secondly, observational effect measurements are often highly unrepresentative of the underlying causal effect because they are skewed by the presence of confounding factors. This is a concern especially in scientific data analysis.

To address these issues, we present a novel descriptive rule discovery approach based on reliably estimating the conditional effect given the potential confounders. We demonstrate that the corresponding score is a conservative and consistent effect estimator, identify the admissible data generation process under which causal rule discovery is possible, and derive an efficient optimization algorithm that successfully detects valuable rules on a multitude of real datasets. Important for both causal and associational data exploration, the presented approach naturally allows for iterative rule discovery, where new non-redundant rules can be found by treating previously discovered rules as confounders in subsequent iterations.

1 Introduction

Determining cause and effect from observational data—that is, from data that was not generated through carefully randomized trials—is among the most important problems in science. Over the years, we have gained a large amount of understanding of what is theoretically possible (Pearl, 2009; Spirtes et al., 2000) which in turn has led to range of methods that, under strict assumptions, can extract partially directed causal graphs from data (Spirtes et al., 2000; Chickering, 2002), up to identify the most likely causal direction between pairs of variables (Shimizu et al., 2006).

Although both impressive and useful, stating that there exists a causal relationship from a set of variables $X$ towards a certain variable of interest $Y$ does not fully satisfy ones curiosity; for a domain expert it is of particular interest to know those conditions under which the effect is visible, such as the specific combinations of drugs that lead to severe side-effects. That is, we are interested in discovering...
causal rules ($\sigma$s) from observational data that consistently maximize rule effect formalized as

$$e(\sigma) = \mathbb{E}[Y \mid \sigma = \text{true}] - \mathbb{E}[Y \mid \sigma = \text{false}] .$$

Though simple to state, this task is not only computationally hard; algorithmic solutions also have to cope with an intricate combination of two semantic problems—one statistical and one structural.

The statistical problem is the well-known phenomenon of overfitting. This phenomenon results from the high variance of the naive empirical (or “plug-in”) estimator of $e$ for rules with too small sample sizes for either of the two events, $\sigma = \text{true}$ or $\sigma = \text{false}$. Combined with the maximization task over a usually very large rule language, this variance turns into a strong positive bias that dominates the search and causes essentially random results of either extremely specific or extremely general rules.

The structural problem is often referred to as Simpson’s paradox: even strong and confidently measured effects of a rule might not actually reflect true domain mechanisms, but can be mere artifacts of the effect of other variables. Notably, such confounding effects can not only attenuate or amplify the marginal effect of a rule on the target variable, in the most misleading cases they can even result in sign reversal.

In this paper, we present a theoretically sound approach to the discovery of causal large effect rules that remedies each of the aforementioned problems.

1. To address the overfitting problem, we propose to measure and optimize the reliable effect of a rule. In contrast to the plug-in estimator, we propose a conservative empirical estimate of the population effect, that is not prone to overfitting. Additionally, and in contrast to other known rule optimization criteria, it is also consistent, i.e., with increasing amounts of evidence (data), the measure converges to the actual population effect of a rule.

2. To address the structural problem, we propose to control for the effect of a given set of potential confounder variables $Z$. In particular, we identify the admissible data generation process under which it is possible to discover truly causal rules. While in practice the set of control variables will rarely be complete, i.e., not contain all potential confounders, this approach can rule out specific alternative explanations of findings as well as eliminate misleading observations caused by selected observables that are known to be strong confounders. In fact, this pragmatic approach is warranted not only by the usual lack of knowledge about the causal structure of the domain, but is also a necessity due to the limited availability of data.

3. We develop a practical algorithm for efficiently discovering the top-$k$ reliable effect rules. In particular, we show how the optimization function can be cast into a branch-and-bound approach based on computationally efficient tight, selection unaware, optimistic estimators.

In sum, we propose a practically applicable rule induction technique that is able to discover true causal rules, and therewith insights to the application domain underlying a dataset. Moreover, our approach lends itself naturally to an iterative data mining approach in which we can discover insights beyond the factors included in $Z$. We support our claims by experiments on real-world datasets as well as by reporting the required computation times on a large set of benchmark datasets.

## 2 Rules for Causal Reasoning

Suppose that we have a population $U$ of individuals $u$. Let $Y$ be a binary target variable, and $X$ be a set of description variables measured on the individuals. Let $Y = \{0, 1\}$ be the domain of $Y$. Let $X_j$ be the domain of a description variable $X_j \in X$, which can be real or categorical. The domain of $X$ is an $m$-dimensional outer product space $\mathcal{X} = X_1 \times \cdots \times X_m$. Let $\pi$ be a set of predicates, where each predicate $\pi \in \pi$ is either an equality or an inequality constraint on one of the description variables $X_j \in X$, e.g. $\pi \equiv X_j < v$ for some threshold $v$. A rule descriptor $\sigma : U \rightarrow \{\text{true, false}\}$ is a logical conjunction of predicates, i.e. $\sigma = \pi_1 \land \pi_2 \land \cdots \land \pi_\ell$ where $\pi_j \in \pi$. We denote by $\mathcal{L}$ the set of all possible rules that can be formulated in this way, also referred to it as rule language.

Let $X_\sigma \subseteq X$ be the subset of description variables over which predicates of $\sigma$ are defined. We denote an intervention on $X_\sigma$, such as setting $X_\sigma$ to a vector value $x$, by a do-expression of the form $\text{do}(X_\sigma = x)$, or simply $\text{do}(x)$ (Pearl, 2009, Chap. 3.4). For a rule $\sigma$, we define an unbiased intervention $\text{do}(\sigma)$ as the randomized operation of satisfying $\sigma$ by setting $X_\sigma$ to some $x$ such that $\sigma(x) = \text{true}$ according to the probabilities $p(X_\sigma = x \mid \sigma = \text{true})$. Our goal is to find those rules $\sigma$
What we can do is approximate the causal effect from observational data by computing the observational effect of \( \sigma \) on \( Y \) under two interventions \( do(\sigma) \) and \( do(\neg \sigma) \), i.e.

\[
e(\text{do}(\sigma)) = E[Y \mid do(\sigma)] - E[Y \mid do(\neg \sigma)]
\]

\[
= p(Y = 1 \mid do(\sigma)) - p(Y = 1 \mid do(\neg \sigma)).
\]

Unfortunately, as we consider observational data, we do not have direct access to these post-intervention distributions. In the following subsection we will identify means by which the causal effect can still be estimated under certain circumstances.

### 2.1 From Observational to Causal Effect

What we can do is approximate the causal effect from observational data by computing the observational effect of \( \sigma \) on \( Y \) by simply conditioning it on \( \sigma = \text{true} \) resp. \( \sigma = \text{false} \), i.e.

\[
e(\sigma) = E[Y \mid \sigma = \text{true}] - E[Y \mid \sigma = \text{false}]
\]

\[
= p(Y = 1 \mid \sigma = \text{true}) - p(Y = 1 \mid \sigma = \text{false}).
\]

However, unless special circumstances hold, the observed conditional probability \( p(Y = 1 \mid \sigma = \text{true}) \) will not be the same as the post-intervention probability \( p(Y = 1 \mid do(\sigma)) \); they are only the same when assignment of values to \( X_\sigma \) is randomized. In observational data, the description variables are seldom randomized, however, and hence we typically have \( e(\sigma) \neq e(\text{do}(\sigma)) \). That is, in general, rule effect measure \( e(\sigma) \) measures association rather than causation.

In particular, we need to be aware that the observed effect of a rule \( \sigma \) on the target \( Y \) may be an artifact due to variations in some other factors (\( Z \)), also called “covariates” or “confounders”, that (co-)cause the observed effect. Formally, a variable \( Z \) is a confounder of \( X \) and \( Y \), if it influences both \( X \) and \( Y \). To illustrate this, let us consider the causal Bayesian network in Fig. 1. Without any knowledge of the causal graph, the effect of a rule \( \sigma \equiv X_1 = 1 \) on variable \( Y \) would be measured as

\[
e(\sigma) = p(Y = 1 \mid \sigma = \text{true}) - p(Y = 1 \mid \sigma = \text{false})
\]

\[
= p(Y = 1 \mid X_1 = 1) - p(Y = 1 \mid X_1 = 0) = 0.75.
\]

However, if we adjust the observed effect using \( Z_1 \)—that is, we partition the data into groups that are homogeneous relative to \( Z_1 \), estimate the effect of \( \sigma \) on \( Y \) in each homogeneous group, then average the results—that influences both \( X_1 \) and \( Y \), we get the adjusted effect of

\[
e_{\text{adj}}(\sigma) = p(Z_1 = 1) (p(Y = 1 \mid X_1 = 1, Z_1 = 1) - p(Y = 1 \mid X_1 = 0, Z_1 = 1)) +
\]

\[
p(Z_1 = 0) (p(Y = 1 \mid X_1 = 1, Z_1 = 0) - p(Y = 1 \mid X_1 = 0, Z_1 = 0)) = 0.15.
\]

In general, confounders can not only amplify or attenuate the marginal effect of \( \sigma \), in the extreme cases we can even observe sign reversal. This phenomenon in which the association between a pair of variables reverses sign when conditioned on the third variable is also known as Simpson’s paradox.

To avoid such paradoxical conclusions, we have to adjust the observational effect for confounders, or more generally all spurious paths (or “back-door” paths) from \( Y \) to \( X_\sigma \), i.e. any undirected path from \( Y \) to any variable \( X_j \in X_\sigma \) that has an incoming edge into \( X_j \) (Pearl, 2009, Chap. 6). We say that a set of variables \( Z \) satisfies the backdoor criterion for \( X_\sigma \) and \( Y \) if it blocks\(^2\) all their

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\(^2\)For the formal definition of “blocking”, please refer to (Pearl, 2009, Def. 1.2.3). For simplicity, we will assume a simplified graphical structure and can simply think of blocking variables as lying on a path.
spurious paths and there is no direct path from \(X_\sigma\) to \(Z\). Given a set of variables \(Z\), with domain \(\mathcal{Z}\), satisfying the back-door criterion, we can estimate the effect of an intervention \(\text{do}(X_\sigma = x)\) on \(Y\) from observational data using the back-door adjustment formula (Pearl, 2009, Thm. 3.3.2), which is given by

\[
p(Y = 1 \mid \text{do}(X_\sigma = x)) = \sum_{z \in \mathcal{Z}} p(Y = 1 \mid X_\sigma = x, Z = z) p(Z = z) \\
= E_Z [E[Y \mid X_\sigma = x, Z]].
\]

In order to perform sound causal rule discovery over the rule language \(\mathcal{L}\) we have to find a set of variables \(Z\) that satisfies the back-door criterion for all descriptive variables. The situation is further complicated by the potential existence of latent variables (\(U\)) in the system. The following definition gives a criterion for an admissible input to causal rule discovery.

**Definition 1** (Admissible Input to Causal Rule Discovery). Let \(X\) be a set of description variables, \(Y\) be a target variable, \(Z\) be a set of control variables, and \(U\) be a set of latent variables. Then \(X, Y,\) and \(Z\) are admissible input to causal rule discovery if the underlying causal graph of the variables satisfies the following:

(a) there are no outgoing edges from \(X\) to \(Z\),
(b) there are no edges between description variables \(X\), and
(c) there are no outgoing edges from the latent variables \(U\) to \(X\).

Such a set \(Z\) is then called an admissible set of control variables.

In Fig. 2, we show the skeleton of causal graph of an input system with an admissible set of control variables. A dashed edge from a node \(u\) to \(v\) indicates that \(u\) potentially affects \(v\). Condition (a) ensures that any intervention on \(X\) does not affect \(Z\). As such, it rules out the possibility of opening a spurious path between \(X\) and \(Y\) via \(Z\) when conditioning on \(Z\)—which can happen in case of a collider structure. By virtue of condition (b), when considering a subset of description variables \(X_\sigma \subset X\), we do not have to condition on the remaining description variables \(X \setminus X_\sigma\) to block any spurious path between \(X_\sigma\) and \(Y\). Condition (c) ensures that, by conditioning on \(Z\), we block any spurious path between \(X\) and \(Y\) via \(U\).

With the definition of admissible control variables we can now state how the causal effect of a rule \(\sigma \in \mathcal{L}\), i.e., the effect of the unbiased intervention \(\text{do}(\sigma)\), can be computed from observational data. Let \(Z\) be a set of control variables. For a rule \(\sigma \in \mathcal{L}\) we define the conditional effect as

\[
e(\sigma \mid Z) = E_Z [E[Y \mid \sigma = \text{true}, Z]] - E_Z [E[Y \mid \sigma = \text{false}, Z]].
\]

As the following theorem shows, this rule measure is indeed capable of capturing the causal effect if the set of controls variables is admissible.

**Theorem 1.** Let \(Z\) be an admissible set of control variables for a target \(Y\), and a set of description variables \(X\). Then, for any rule \(\sigma \in \mathcal{L}\), we have \(e(\sigma \mid Z) = e(\text{do}(\sigma))\).

Exceptional cases aside, in practice, we often do not know the complete causal diagram, and hence do not know if we are considering—or have even measured—all of \(Z\). In an attempt to block any path other than the direct ones between \(X\) and \(Y\), a naive approach would be to include as many variables in \(Z\) as possible. This, however, likely leads to measuring association rather than causation. A second problem, which will be discussed in the next section, is that the more control variables we consider, the more the confidence of our estimate of the conditional effect is reduced. In short, we need to be careful in selecting \(Z\).

One strategy would be to initialize \(Z\) with our best guess, which could be the empty set, and then discover the rules with the strongest conditional effect. From these, we can then carefully select...
We address this problem of high variance by introducing bias to the plugin-estimator. In particular, we introduce bias in terms of our confidence in the point estimates using confidence intervals. Note we show the score distribution for the plug-in estimator for a very specific rule of five conditions, \( \hat{Y} \).

Taking a conservative approach, we bias the difference \( \hat{Y} \) where

\[
\hat{Y} = \hat{p}(\sigma = 1 | \sigma = \text{true}, Z = z) - \hat{p}(\sigma = 1 | \sigma = \text{false}, Z = z)
\]

\( \hat{p}(\sigma = 1 | \sigma = \text{true}, Z = z) \)

...and see that while it is close to the true conditional effect, it shows very high variance in small samples. This high variance is problematic, as it leads to overfitting: if we use this estimator for the optimisation task over a very large space of rules, the variance will turn into a strong positive bias—we will overestimate the effects of rules from the sample—that dominates the search, and we end up with random results of either extremely specific or extremely general rules.

We address this problem of high variance by introducing bias to the plugin-estimator. In particular, we introduce bias in terms of our confidence in the point estimates using confidence intervals. Note that we need not quantify the confidence of the point estimate \( \hat{p}(z) \) as \( \hat{p}(z) = p(z) \); the point estimates of particular concern are simply the empirical conditional probability mass functions \( \hat{p}(Y = 1 | \sigma = \text{true}, Z = z) \), and \( \hat{p}(Y = 1 | \sigma = \text{false}, Z = z) \).

In repeated random samples of units with \( \sigma = \text{true} \) and \( Z = z \), the number of units with outcome \( Y = 1 \) is a binomial random variable with the success probability \( \hat{p}(Y = 1 | \sigma = \text{true}, Z = z) \). Let \( n_s \) be the number of successes in \( n \) trials. The one-sided confidence interval of the probability of success, \( q = n_s/n \), of a binomially distributed observation, using a normal approximation on the distribution of error, is hence \( \beta \sqrt{q(1-q)/n} \), where \( \beta \) is the \( 1 - \alpha/2 \) quantile of a standard normal distribution for an error rate \( \alpha \). For the 95% confidence level, the error rate is \( \alpha = 0.05 \), thereby \( \beta = 1.96 \). Observe that the maximum value of \( q(1-q) \) is 1/4, and hence the maximum value of the one-sided confidence interval is \( \beta/(2\sqrt{n}) \).

Taking a conservative approach, we bias the difference \( \hat{p}_\sigma - \hat{p}_{\sim \sigma} \) by subtracting the sum of the maximum values of the one-sided confidence intervals of the point estimates. In a control group \( Z \), let \( n_{s} \) be the number of data points that satisfy \( \sigma = \text{true} \), and \( n_{\sim \sigma} \) be the number of remaining data points that satisfy \( \sigma = \text{false} \). Then the confidence interval corrected difference \( \hat{p}_\sigma - \hat{p}_{\sim \sigma} \) is given by

\[
\tau(\sigma, Z) = (\hat{p}_\sigma - \hat{p}_{\sim \sigma}) - \left( \beta/(2\sqrt{n}_\sigma) + \beta/(2\sqrt{n}_{\sim \sigma}) \right).
\]

Note that \( \tau(\sigma, Z) \) lower bounds the true probability mass difference in the population with confidence 1 - \( \alpha \). That is, there is a 1 - \( \alpha \) chance that the true difference is larger than \( \tau(\sigma, Z) \). For a fixed \( \beta \),
we generate the population using the causal graph in Fig. 1. In addition, we generate five uniformly

\[ \hat{r}(\sigma | \mathbf{z}) = \sum_{\mathbf{z} \in \mathcal{Z}} \hat{p}(\mathbf{z}) \tau(\sigma, \mathbf{z}) . \]

Although biased, \( \hat{r}(\sigma | \mathbf{Z}) \) is still a consistent estimator of the conditional effect. Importantly, in contrast to the plug-in estimator, the reliable estimator is much better at generalisation as it avoids overfitting.

Consider the following example to see the generalisation behaviour of the estimators. Suppose that we generate the population using the causal graph in Fig. 1. In addition, we generate five uniformly distributed binary description variables, \( X_2, X_3, \ldots, X_6 \) that are independent of each other as well as the rest of the variables. We can now numerically estimate the variance of the two estimators for a specific rule, such as \( \rho' = X_1 = 1 \land X_2 = 0 \land X_3 = 1 \land X_4 = 0 \land X_5 = 1 \), which does not only contain truly causal attribute \( X_1 \) but also other four attributes that are independent of the target \( Y \).

To do so, we draw stratified samples of increasing sizes from the population, and report \( \hat{r}(\sigma | \mathbf{Z}) \) and \( \hat{r}(\sigma | \mathbf{Z}) \) scores averaged over 25 simulations along with one sample standard deviation in Fig. 4 (left). We observe that variances of both estimators decrease with increasing sample size. Although the reliable estimator is biased, its variance is relatively low compared to the plug-in estimator. As a result of this low variance, unlike the plug-in estimator, the reliable estimator is indeed able to avoid overfitting, and hence, better at generalisation. Let \( \sigma^* \) be the top-1 rule in the population, i.e. \( \sigma^* = \arg\max_{\sigma \in \mathcal{L}} \epsilon(\sigma | \mathbf{Z}) \). Let \( \phi' = \arg\max_{\sigma \in \mathcal{L}} \epsilon(\sigma | \mathbf{Z}) \), and \( \rho^* = \arg\max_{\sigma \in \mathcal{L}} \hat{r}(\sigma | \mathbf{Z}) \). In Fig. 4 (right), we plot \( \epsilon(\phi' | \mathbf{Z}) \) against \( \epsilon(\rho^* | \mathbf{Z}) \). We observe that with increasing sample sizes \( \epsilon(\rho^* | \mathbf{Z}) \) is both relatively closer, as well as converges much faster to the reference \( \epsilon(\sigma^* | \mathbf{Z}) \), which is in agreement with both theory and intuition.
3 Discovering Rules

Now that we have a reliable and consistent score for the conditional effect, we turn to the problem of discovering rules that yield maximal reliable conditional effect. Below, we provide the formal problem definition.

**Definition 2 (Top-k causal rule discovery).** Given a sample $S$, and a positive integer $k$, find the set $F_k \subseteq \mathcal{F}_k$, such that for all $\sigma \in F_k$ and $\sigma' \in \mathcal{L} \setminus F_k$, $\tilde{r}(\sigma | Z) \geq \tilde{r}(\sigma')$.

Given the hardness of empirical effect maximisation problems (Wang et al., 2005), it is unlikely that the optimisation of the reliable conditional effect allows a worst-case polynomial algorithm. While the exact computational complexity of the causal rule discovery problem is open, here we proceed to develop a practically efficient algorithm using the branch-and-bound paradigm, which is a standard approach in rule discovery.

3.1 Branch-and-Bound Search

The branch-and-bound search scheme (Mehlhorn and Sanders, 2008, Ch. 12) provides a systematic way for efficient exhaustive search by restricting the exploration to promising candidates only. More formally, the goal of branch-and-bound is to find a solution $S$ that optimizes the objective function $f : \Omega \to \mathbb{R}$, among a set of admissible solutions $\Omega$, also called the search space. Let $\text{ext}(\sigma)$, also called the extension of a rule $\sigma$, be the the subset of data points in a sample described by $\sigma$, defined as $\text{ext}(\sigma) = \{ u \in S | \sigma(u) = \text{true} \}$. Then the generic search scheme requires the following two ingredients (Boley et al., 2017):

- A refinement operator $r : \mathcal{L} \to \mathcal{P}(\mathcal{L})$ that is monotone, i.e. for $\sigma, \varphi \in \mathcal{L}$ with $\varphi = r(\sigma)$ it holds that $\text{ext}(\varphi) \subseteq \text{ext}(\sigma)$, and that non-redundantly generates the search space $\mathcal{L}$. That is, for every rule $\sigma \in \mathcal{L}$, there is a unique sequence of rules $\sigma_0, \sigma_1, \ldots, \sigma_t = \sigma$ with $\sigma_i = r(\sigma_{i-1})$.
- An optimistic estimator $\hat{f} : \Omega \to \mathbb{R}$ that provides an upper bound on the objective function attainable by extending the current rule to more specific rules. That is, it holds that $f(\sigma) \geq \hat{f}(\varphi)$ for all $\varphi \in \mathcal{L}$ with $\text{ext}(\varphi) \subseteq \text{ext}(\sigma)$.

A branch-and-bound algorithm simply enumerates the search space $\mathcal{L}$ starting from the root $\phi$ using the refinement operator $r$ (branch), but based on the optimistic estimator $\hat{f}$ prunes those branches that cannot yield improvement over the best rules found so far (bound). Depending on the branching operator, solutions may be reachable via multiple paths. To avoid evaluating solutions multiple times, more advanced implementations of branch-and-bound enumerate the search space non-redundantly, for example by considering only closures (Uno et al., 2003; Boley and Grosskreutz, 2009).

The optimistic estimator depends on the objective function. Interestingly, there are many optimistic estimators for an objective function $f$. Not all of these are equally well-suited in practice, as the tightness of the optimistic estimator determines its pruning potential. The ideal choice would therefore be the strictest optimistic estimator, which takes the maximum over all possible refinements of $\sigma$, i.e. $\hat{f}(\sigma) = \max \{ f(\varphi) | \text{ext}(\varphi) \subseteq \text{ext}(\sigma) \}$. Computing this estimator, however, is as hard as the original optimisation problem itself, and therefore not a practical solution. As the...
We see that, regardless of \( \pi \), we can write
\[
\bar{\pi}
\]
where
\[
\left(\begin{array}{c}
\sum \ n_1 \\
\sum \ n_0
\end{array}\right)
\]
This suggests that we can get a
\[
\hat{\pi}
\]
To develop optimistic estimators for the reliable estimator \( \hat{\pi} \), we first review its definition first,
\[
\hat{\pi}(\sigma | Z) = \sum_{\nu \in Z} \hat{\nu}(\sigma, Z).
\]
We see that, regardless of \( \sigma, \hat{\nu}(\sigma, Z) \) remains the same for all control groups \( z \in Z \). This implies we can obtain an optimistic estimator of \( \hat{\pi}(\sigma | Z) \) by simply bounding \( \tau(\sigma, Z) \) for all \( z \in Z \). The optimistic estimator of \( \hat{\pi}(\sigma | Z) \) is hence given by
\[
\bar{\pi} = \sum_{\nu \in Z} \bar{\nu}(\sigma, Z),
\]
where \( \bar{\nu}(\sigma, Z) \) is the optimistic estimator of \( \tau(\sigma, Z) \) yet to be defined. To derive optimistic estimators \( \bar{\nu}(\sigma, Z) \), for clarity of exposition we first project \( \tau(\sigma, Z) \) in terms of free variables \( a \) and \( b \), such that we can write
\[
\tau(a, b) = \frac{a + 1}{a + b + 2} - \frac{n_1 - a + 1}{n - a - b + 2} - \frac{\beta_c}{2\sqrt{a + b + 2}} - \frac{\beta_c}{2\sqrt{n - a - b + 2}}.
\]
Suppose that we have a contingency table as shown in Fig. 5 (left) for a control group \( z \) with a rule \( \sigma \). The refinement of \( \tau(\sigma, Z) \) results in a contingency table as shown in Fig. 5 (right). Note that \( n_1, n_0 \), and \( n \) do not change within a group regardless of a rule. Now, since \( \text{ext}(\sigma') \subseteq \text{ext}(\sigma) \) for any \( \sigma' = \nu(\sigma) \), we have the following relations: \( a' \leq a \) and \( b' \leq b \). This implies that the subsets of the extensions of \( \sigma \) will have contingency table counts \( a' \) in the range \( \{0, 1, \ldots, a\} \), and \( b' \) in the range \( \{0, 1, \ldots, b\} \). Let \( C = \{0, 1, \ldots, a\} \times \{0, 1, \ldots, b\} \). Then the optimistic estimator of \( \tau(\sigma, Z) \) can be defined in terms of \( C \) as
\[
\bar{\tau}(\sigma, Z) \geq \max_{(a', b') \in C} \tau(a', b').
\]
This suggests that we can get a tight optimistic estimate of \( \tau(\sigma, Z) \) by simply taking the maximum value of \( \tau \) from all possible configurations \( C \) in linear time. If possible, however, an improvement over this is always desirable. It turns out that we can speed up the computation of the tight optimistic estimator, which we formalize in the following proposition.
Proposition 1. Let \( C = \{0, 1, \ldots, a\} \times \{0, 1, \ldots, b\} \) be the set of all possible configurations of \((a', b')\) in Fig. 5 (right) that can result from the refinement of a rule \( \sigma \) from the contingency table of Fig. 5 (left). Then the tight optimistic estimator of \( \tau(\sigma, z) \) is given by

\[
\bar{\tau}_t(\sigma, z) = \max_{a' \in \{0, 1, \ldots, a\}} \frac{a' + 1}{a' + 2} - \frac{n_1 - a' + 1}{n - a' + 2} - \frac{\beta_c}{2\sqrt{a' + 2}} - \frac{\beta_c}{2\sqrt{n - a' + 2}}.
\]

4 Related Work

In rule-based classification the goal is to find a (set of) rules that together optimally predict the target label. Classic approaches include CN2 (Lavrac et al., 2004), and FOIL (Quinlan and Cameron-Jones, 1995). In more recent work, the attention shifted from accuracy to optimizing more reliable scores, such as Area-Under-ROC (Fürnkranz and Flach, 2005). While related, the overall goal in learning classification rules is different than ours; we want to find rules that describe the strong causal effects, rather than separate two classes.

Association rules (Agrawal et al., 1993) are such rules, taking the form \( x \rightarrow y \), where \( x \) is a set of items, and \( y \) is a target item. The interestingness of an association rule is typically measured in terms of its relative occurrence frequency. To get reliable rules, we can impose hard constraints on the relative occurrence frequency of an association rule. Despite that, within this framework we conflate the goal of finding rules with large effect size with the relative occurrence frequency of the rule. Contrast patterns (Dong and Li, 1999; Dong and Bailey, 2012), otherwise known as emerging patterns, are patterns whose supports differ significantly between datasets. As the support of a pattern is an empirical effect measure, without special measures such as taken here, emerging patterns tend to overfit the given sample and hence capture unreliable statements that are not necessarily characteristic of the underlying domain.

Subgroup discovery (Atzmueller, 2015) is a related, but subtly different task. Most subgroup discovery methods optimize a surrogate function based on some statistical null hypothesis test. The resulting objective function are usually some multiplicative combination of coverage and effect and, hence, do not consistently optimize for large effect. Also patterns found through standard subgroup discovery frameworks do not correct for the influence of confounder and are hence purely associational. Closer to our approach is RAWR (Kalofolias et al., 2017), which discovers patterns that both have large deviation from the mean of the population, but at the same time are also representative with respect to a univariate binary control variable \( z \) in terms of statistical parity. Besides that we introduce a reliable measure of effect, our framework allows for control variables of higher dimensionality that, under the specific circumstances, directly optimizes the causal effect.

Causal falling rule lists (Wang and Rudin, 2017) are sequences of “if-then” rules over the covariates such that the treatment effect decreases monotonically down the list. Our formulation, on the other hand, is aimed at finding top-\( k \) interventions, represented by rules, that have maximal effect on the target given \( Z \). Atzmueller and Puppe (2009) propose a semi-automatic approach to discovering causal interactions by mining subgroups, inferring a causal network over these, and visually presenting this to the user. Li et al. (2015) are specifically concerned with discovering causal association rules from observational data. They propose to do so by first mining association rules, and then performing cohort studies per rule. Unlike our setup, the scores they optimize are not statistically consistent.

Overall, despite the importance of the problem, to the best of our knowledge there does not exist a generally applicable, theoretically well-founded, efficient, and reliable approach to discovering rules with strong causal effect from observational data.

5 Experiments

We implemented the branch-and-bound search algorithm in free and open source realKD\(^3\) Java library, and provide the source code online.\(^4\) We use a priority-queue based implementation of branch-and-bound search. All experiments were executed single threaded on Intel Xeon E5-2643 v3

\(^3\)https://bitbucket.org/realKD/
\(^4\)https://goo.gl/tcntcT
We studied the problem of discovering reliable causal rules from observational data. Whereas we observe that the branch-and-bound search with the tight optimistic estimator retrieves the optimal rule discovered in the first iteration is used as a control variable. We report the control variables (\(Z\)) used in that run, and the optimal top-1 rule along with their coverage, followed by \(\hat{r}(\sigma \mid Z)\) and \(\hat{e}(\sigma \mid Z)\) scores. We start without control variables in the first iteration. In the subsequent iterations, we put the top-1 rules discovered from previous iterations in \(Z\).

In the first iteration, without any control variables, we observe that being a female passenger (\(\text{sex=female}\)) with the first, or the second class ticket (\(\text{class} \leq 2\)) has the highest effect on survival with a score of \(\hat{r}(\sigma \mid Z) = 0.576\). It is well-known that passengers from different classes were treated differently during evacuation. What is interesting is that although females were more likely to survive, this only applied to the females from the first and the second class; this is also corroborated by the fact that roughly half of the females from the third class did not survive the mishap compared to the one-tenth from the other classes combined.

In the second iteration, the top-1 rule discovered in the first iteration is used as a control variable. We find that children (\(\text{age} < 12.5\)) with fewer siblings (\(\text{sib-sp} \leq 2\)), and parents on board (\(\text{par-ch} \geq 1\)) have highest effect on survival. The fact that this rule came out on top with a coverage of only 4.6% demonstrates that the proposed method can discover rare rules.

In the third iteration, after controlling for the top-1 rules discovered from the previous two iterations, we find that unmarried females (\(\text{title=Miss}\)) despite paying a low fare (\(\text{fare} < 19.85\)) have the highest effect on survival with a score of \(\hat{r}(\sigma \mid Z) = 0.003\). In the fourth iteration, we find that the top-3 rules have negative \(\hat{r}(\sigma \mid Z)\) scores. Although the \(\hat{e}(\sigma \mid Z)\) score is positive for the top-1 rule, the negative \(\hat{r}(\sigma \mid Z)\) score indicates that there is no evidence. Therefore we stop after the fourth iteration.

6 Conclusions

We studied the problem of discovering reliable causal rules from observational data. Whereas traditional descriptive rule discovery methods struggle with the consistent detection of conditions

\footnote{https://www.kaggle.com/c/titanic/data}
under which a strong effect on an output variable of interest happens. Instead, we presented a novel
descriptive rule discovery approach based on reliably estimating the conditional effect given the
value of potential confounders. We demonstrated that the corresponding score is a conservative and
consistent effect estimator, identified the admissible data generation process under which causal
rule discovery is possible, and derived an efficient optimization algorithm that successfully detects
valuable rules on a multitude of real datasets. Through empirical evaluation we showed our framework
is efficient and applicable on datasets of realistic sizes and dimensions. Moreover, and of particular
importance for both causal and associational data exploration, we showed that the presented approach
naturally allows for iterative rule discovery.

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11


Proof of Theorem 1

Proof. By condition (b), $Z$ also satisfies the back-door criterion for any subset of description variables $X_\sigma \subset X$ and $Y$. Thus the effect of $do(\sigma)$ on the probability of $Y = 1$ can be computed using the back-door adjustment formula as

$$p(Y = 1 \mid do(\sigma)) = \sum_{x: \sigma(x) = \text{true}} p(Y = 1 \mid do(X_\sigma = x)) p(X_\sigma = x \mid \sigma = \text{true})$$

$$= \sum_{x: \sigma(x) = \text{true}} E_Z [p(Y = 1 \mid X_\sigma = x, Z)] p(X_\sigma = x \mid \sigma = \text{true})$$

using the linearity of expectation, the definition of joint probability, and that $p(X_\sigma = x, \sigma = \text{true}) = p(X_\sigma = x)$ for $x$ with $\sigma(x) = \text{true}$, this results in

$$= E_Z \left[ \sum_{x: \sigma(x) = \text{true}} p(Y = 1 \mid X_\sigma = x, Z) p(X_\sigma = x) \right]_{\sigma = \text{true}}$$

$$= E_Z \left[ \sum_{x: \sigma(x) = \text{true}} p(Y = 1, X_\sigma = x \mid Z) \right]_{\sigma = \text{true}}$$

$$= E_Z [p(Y = 1 \mid \sigma = \text{true}, Z)]$$

$$= E_Z [E[Y \mid \sigma = \text{true}, Z]].$$

Similarly the effect of $do(-\sigma)$ on the probability of $Y = 1$ can be computed as

$$p(Y = 1 \mid do(-\sigma)) = E_Z [E[Y \mid \sigma = \text{false}, Z]].$$

Combining the two, we get

$$e(\sigma \mid Z) = E_Z [E[Y \mid \sigma = \text{true}, Z]] - E_Z [E[Y \mid \sigma = \text{false}, Z]]$$

$$= p(Y = 1 \mid do(\sigma)) - p(Y = 1 \mid do(-\sigma))$$

$$= e(\sigma(\sigma)).$$

\[\Box\]

Proof of Proposition 1

Proof. The expression for $\tau(a', b')$ from the contingency table in Fig. 5 (right) is given by

$$\tau(a', b') = \frac{a' + 1}{a' + b' + 2} - \frac{n_1 - a' + 1}{n - a' - b' + 2} - \frac{\beta_c}{2 \sqrt{a' + b' + 2}} - \frac{\beta_c}{2 \sqrt{n - a' - b' + 2}}.$$

Combining the first and the third term above, we get

$$\lambda_z(a', b') = \frac{2a' + 2 - \beta_c \sqrt{a' + b' + 2}}{2(a' + b' + 2)} - \frac{n_1 - a' + 1}{n - a' - b' + 2} - \frac{\beta_c}{2 \sqrt{n - a' - b' + 2}}.$$

Note that if we fix the value of $a'$, then the value of $b'$ that maximises $\tau(a', b')$ has to maximise the first term above, but minimise the other two terms. Observe that $b' = 0$, out of $b' \in \{0, 1, \ldots, b\}$, does both simultaneously. Thus we have the following relation.

$$\tau(a', 0) > \tau(a', b') \text{ for all } b' > 0.$$

Then the tight optimistic estimator of $\tau(\sigma, z)$ is the maximum value over all possible configurations $C$ given by

$$\bar{\tau}(\sigma, z) = \max_{a' \in \{0, 1, \ldots, a\}} \tau(a', 0)$$

$$= \max_{a' \in \{0, 1, \ldots, a\}} \frac{a' + 1}{a' + 2} - \frac{n_1 - a' + 1}{n - a' + 2} - \frac{\beta_c}{2 \sqrt{a' + 2}} - \frac{\beta_c}{2 \sqrt{n - a' + 2}}.$$

\[\Box\]
## Efficiency Results on Benchmark Datasets

Table 2: Summary of the datasets used for the evaluation along with the results. For each dataset, we report the target variable \( (Y) \), the control variables \( (Z) \), the number of rows \( (N) \), the number of description variables \( (m) \), the approximation factor \( \gamma \) for the branch-and-bound implementation to finish within an hour, the runtime in seconds, and the number of nodes expanded during the search.

<table>
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<tr>
<th>Dataset</th>
<th>Target ((Y))</th>
<th>Controls ((Z))</th>
<th>(N)</th>
<th>(m)</th>
<th>(\gamma)</th>
<th>time (s)</th>
<th>#nodes</th>
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