In the Eye of the Beholder: Robust Prediction with Causal User Modeling

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Abstract

Accurately predicting the relevance of items to users is crucial to the success of many social platforms. Conventional approaches train models on logged historical data; but recommendation systems, media services, and online marketplaces all exhibit a constant influx of new content—making relevancy a moving target, to which standard predictive models are not robust. In this paper, we propose a learning framework for relevance prediction that is robust to changes in the data distribution. Our key observation is that robustness can be obtained by accounting for *how users causally perceive the environment*. We model users as boundedly-rational decision makers whose causal beliefs are encoded by a causal graph, and show how minimal information regarding the graph can be used to contend with distributional changes. Experiments in multiple settings demonstrate the effectiveness of our approach.

1 Introduction

Across a multitude of domains and applications, machine learning has become imperative for guiding human users in many of the decisions they make [44,58,10]. From recommendation systems and search engines to e-commerce platforms and online marketplaces, learned models are regularly used to filter content, rank items, and display select information—all with the primary intent of helping users choose items that are relevant to them. The predominant approach for learning in these tasks is to train models to accurately predict the relevance of items to users, but since training is often carried out on logged historical records, even highly-accurate models remain calibrated to the distribution of *previously* observed data on which they were trained [7,59,56]. Given that in virtually any online platform the distribution of content naturally varies over time and location—due to trends and fashions, innovation, or forces of supply and demand—models trained on logged data may fail to correctly predict the choices and preferences of users on unseen, future distributions [12,1,18,27,34].

In this paper, we present a novel conceptual framework for learning predictive models of user-item relevance that are robust to changes in the underlying data distribution. Our approach is built around two key observations: (i) that relevance to users is determined by the way in which users *perceive* value, and (ii) that this process of value attribution is *causal* in nature. As an example, consider a video streaming service in which a user u is trying to determine whether watching a certain movie will be worthwhile. To make this decision, $y \in \{0, 1\}$, the user has at her disposal a feature description of the movie, x, and a system-generated, personalized relevance score, r (e.g., "a 92% match!"). How will she integrate these two informational sources into a decision? We argue that this crucially hinges on her belief as to *why* a particular relevance score is coupled to a particular movie. For example, if a movie boasts a high relevance score, then she might suppose this score was given *because* the system believes the user would like this movie. Another user, however, may reason differently, and instead believe that high relevance scores are given *because* movies are sponsored; if she suspects this to be a likely scenario, her reasoning should have a stark effect on her choices. In both cases

Submitted to 36th Conference on Neural Information Processing Systems (NeurIPS 2022). Do not distribute.

above, perceived values (and the actions that follow) stem from how each user causally interprets the recommendation environment, and the underlying causal structure determines how belief regarding value changes, or does not, in response to changes in important variables (e.g., in u, x, or r).

Here, we show how knowledge regarding the causal perceptions of users can be leveraged for providing distributional robustness in learning. A primary concern for robust learning is the reliance of predictions on spurious correlations [3]; here we argue that spuriousness can *result* from causal perceptions underlying user choice behavior. To see the relation between causal perceptions and spuriousness, assume that in our movies example above, the training data exhibits a strong correlation between users' choices of movies, y, and a 'genre' feature, x_g. A predictive model optimized for accuracy will likely exploit this association, and rely on x_g for prediction. Now, further assume that what *realy* drives user satisfaction is 'production quality', x_q; if x_g and x_q are *spuriously* correlated in the training data, then once the distribution of genres naturally changes over time, the predictive model can fail: the association between x_g and y, on which predictions rely, may no longer hold.

In essence, our approach casts robust prediction of personalized relevance as a problem of out-of-distribution (OOD) learning, but carefully tailored to settings where data generation is governed by users' causal beliefs and corresponding behavior. There is a growing recognition of how a causal understanding of the learning environment can improve cross-domain generalization [3,55]; our key conceptual contribution is the observation that, in relevance prediction, users' perceptions *are* the causal environment. Thus, there is no 'true' causal graph—all is in the eye of the beholder. To cope with this, we model users as reasoning about decisions through a causal graph [35,47]—thus allowing our approach to anticipate how changes in the data translate to changes in user behavior.

Building on this idea, as well as on recent advances in the use of causal modeling for out-of-distribution learning [3,55,54], we show how various levels of knowledge regarding users' causal beliefs can be utilized for learning distributionally robust predictive models. To encourage predictions $\hat{y}$ to be invariant to changes in the environment e, our approach enforces independence between $\hat{y}$ and e (possibly given y). This is achieved with regularization [22]. In general, different graphs require different regularization [54]; unfortunately, inferring user graphs is likely to be costly (if using randomized experiments) and challenging (if using observational data). Our key observation is that, for user graphs, it suffices to know which of two *classes* the graph belongs to—*causal* or *anti-causal*— determined by the direction of edges between x, r and y (Fig. 1a). The user's class, which is easier to infer, determines the regularization scheme.

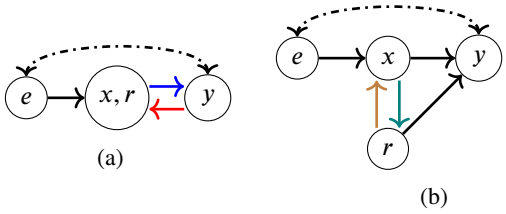

Figure 1: Simplified graphs describing users of different: (a) *classes*: *causal* or *anti-causal*, and (b) *sub-classes*: *believer* or *skeptic* (here shown for a causal user). Dashed lines indicate possible spuriousness (e.g., via selection).

Nonetheless, more fine-grained information can still be useful. We show the following novel result: if two users generate the same data, but differ in their underlying graph, they will have different optimal *out-of-distribution* models. The reason for this is that, to achieve robustness, regularizing for independence will result in the discarding of different information for each user. Operationally, this means that learning should include different models for each user-type (not doing so implicitly constrains the models to be the same). Here again we show that minimal additional information is useful, and focus on subclasses of graphs that differ only in the direction of the edges between x and r (Fig. 1b); nonetheless, our result applies broadly and may be of general interest for causal learning.

We end with a thorough empirical evaluation of our approach (§5), where we explore the benefits of different forms of knowledge regarding users' causal beliefs: whether they are *casual* or *anti-causal*, and the directionality of $x \leftrightarrows r$. Importantly, our results also imply that *not* accounting for causal aspects of user decision-making, or modelling them wrongly, can result in poor OOD performance. As systems often also play a role in determining what information is presented to users (e.g., providing r), understanding possible failure modes—and how to obtain robustness—becomes vital.

Broader aims. We aim to promote within machine learning the idea of modeling users as active and autonomous decision-makers, with emphasis on capturing realistic aspects of human decision-making. Our approach crucially hinges on modelling users as decision-makers that (i) reason *causally*, (ii) are

boundedly-rational, and (iii) must cope with *uncertainty*. As we will show, all three are key to our framework, and operate in unison. Each of the aspects above relates to one of three main pillars on which modern theories of decision-making stand [46], thus blending three different fields—discrete choice (economics), causal modeling (statistics), and domain generalization (machine learning).

2 Related Work

Causality and Recommendations. Formal causal inference techniques have been used extensively in many domains, but have only recently been applied to recommendations [29,57,7,59,56]. Liang et al. [30] use causal analysis to describe a model of user exposure to items. Some work has also been done to understand the causal impact of these systems on behavior by finding natural experiments in observational data [43,50,40], and through simulations [11,39]. Bottou et al. [8] use causally-motivated techniques in the design of deployed learning systems for ad placement to avoid confounding. As most of this literature addresses selection bias and the effect of recommendations on user behavior [7,59,56], there is no work, as far as we know, that models boundedly rational agents interacting with a recommender system. Moreover, we are the first to propose modeling users' (mis)perceptions about the recommendation generation process using causal graphs.

Bounded Rationality and Subjective Beliefs. The bounded rationality literature focuses on modelling agents that make decisions under uncertainty, without the ability to fully process the state of the world, and therefore hold subjective beliefs about the data-generating process. Eyster and Rabin [17] defined *cursed beliefs*, which capture an agent's failure to realize that his opponents' behavior depends on factors beyond those he is informed of. Building on Esponda and Pouzo [16], who modelled equilibrium beliefs under misspecified subjective models, Spiegler [47] used causal graphs to analyze agents that impose subjective causal interpretations on observed correlations. This work lays the foundation upon which we model users here, and has sprouted many interesting extensions [14,15].

Causality and Invariant Learning. Correlational predictive models can be untrustworthy [24], and latch onto spurious correlations, leading to errors in OOD settings [33,20,19]. This shortcoming can potentially be addressed by a causal perspective, as knowledge of the causal relationship between observations and labels can be used to mitigate predictor reliance on them [9,54]. In our experiments, we learn a representation that is invariant to interventions on the 'environment' e, a special case of an invariant representation [3,28,4]. Learning models which generalize OOD is a fruitful area of research with many recent developments [31,23,36,51,5,55]. Recently, Veitch et al. [54] showed that the means and implications of invariant learning depend on the data's true causal structure. Specifically, distinct causal structures require distinct regularization schemes to induce invariance.

3 Modelling Approach

3.1 Learning Setting

In our setting, data consists of users, items, and choices. Users are described by features $u \in \mathbb{R}^{d_u}$, and items are described by two types of features: intrinsic item properties, $x \in \mathbb{R}^{d_x}$ (e.g., movie genre, plot synopsis, cast and crew), and information provided by the platform, $r \in \mathbb{R}^{d_r}$ (e.g., recommendation score, user reviews). We will sometimes make a distinction between features that are available to users, and those that are not; in such cases, we denote unobserved features by $\bar{x}$, and with slight abuse of notation, use x for the remaining observed features (we assume r is always observed). Choices $y \in \{0, 1\}$ indicate whether a user u chose to interact (e.g., click, buy, watch) with a certain item (x, r). Tuples (u, x, r, y) are sampled iid from certain unknown joint distributions, which we define next.

As we are interested in robustness to distributional change, we follow the general setup of *domain generalization* [6,26,5,55] in which there is a collection of environments, denoted by a set $\mathcal{E}$, and each environment $e \in \mathcal{E}$ defines a different joint distribution D^e over (u, x, r, y). We assume there is training data available from a subset of K environments, $\mathcal{E}_{\text{train}} = \{e_1, \dots, e_K\} \subset \mathcal{E}$, with datasets $S_k = \{(u_{ki}, x_{ki}, r_{ki}, y_{ki})\}_{i=1}^{m_k}$ drawn i.i.d from the corresponding D^{e_k}. We denote the pooled training distribution by $D_{\text{train}} = \cup_{e \in \mathcal{E}_{\text{train}}} D^e$ and the pooled training data by $S = \cup_k S_k$ with $m = \sum_k m_k$.

Our goal is to learn a robust predictive model $\hat{y} = f(u, x, r; \theta) := f_u(x, r; \theta)$ with parameters θ; the f_u notation will be helpful in our discussion of robustness as it emphasizes our focus on individual users. We now turn to define the precise type of robustness that we will be seeking.

Robustness via causal graphs. The type of robustness that we would like our model to satisfy is *counterfactual invariance* (CI) [54]. Denoting $x(e), r(e)$ as the counterfactual features that would have been observed had the environment been set to e, this is defined as:

Definition 1. *A model f_u is CI if $\forall e, e' \in \mathcal{E}$ it holds a.e. that $f_u(x(e'), r(e'); \theta) = f_u(x(e), r(e); \theta)$.*

The challenge in obtaining CI predictors is that at train time we only observe a subset of the environments, $\mathcal{E}_{\text{train}} \subset \mathcal{E}$, while CI requires independence to hold for *all* environments $e \in \mathcal{E}$. To reason formally about the role of e in the data generating process, and hence about the type of distribution shifts under which our model should remain invariant, it is common to assume that a causal structure underlies data generation [23,3]. This is often modeled as a (directed) causal graph [35]; robustness is then defined as insensitivity of the predictive model to changes (or 'interventions') in the variable e, which can trigger changes in other variables that lie 'downstream' in the graph. Fig. 2 illustrates how a graph can reveal a risk of spuriousness: if an edge $e \to y$ exists, then in learning $y \approx f(x, r)$, information in x, r that correlates with e can (erroneously) be used to explain y; once e changes, this relation breaks. To encourage robustness, a common approach is to construct a learning objective that avoids spurious correlations by enforcing certain conditional independence relations to hold, e.g., via regularization (see §4). The question of *which* relations are required can be answered by examining the graph and the conditional independencies it encodes (between e, x, r, y, and $\hat{y}$). Unfortunately, inferring the causal graph is in general hard; however, determining the 'correct' learning objective may require only partial information regarding the graph. We will return to the type of information we require for our purposes, and the precise ways in which we use it, in §4.

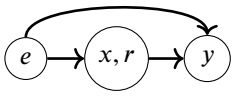

Figure 2: A causal graph describing how e can generate a spurious correlation. If $\hat{y} = f(x, r)$ is trained on one e and optimized for in-domain performance, then once e changes, $\hat{y}$ no longer explains y.

3.2 Users as decision makers

Focusing on relevance prediction, at the heart of our approach lies the observation that what underlies the generating process of data, and in particular of labels, *is the way in which users causally perceive the environment*. In this sense, users *are* the causal mechanism, and their causal perceptions manifest in their decision-making. Operationally, we model users as acting on the basis of *individualized causal graphs* [47] that define how changes in one variable propagate to influence others, and ultimately—determine choice behavior. This allows us to anticipate, target, and account for sources of spuriousness.

Rational users. To see how modeling users as causal decision-makers can be helpful, consider first a conventional 'correlative' approach for training f_u, e.g. by minimizing the loss of a corresponding score function $v_u(x, r) = v(u, x, r)$, and predicting via $\hat{y} = \text{argmax}_{y \in \{0,1\}}\, y v_u(x, r) = \mathbb{1}\{v_u(x, r) > 0\}$. From the perspective of user modeling, v_u can be interpreted as a personalized 'value function'; this complies with classic Expected Utility Theory (EUT) [53], in which users are modeled as rational agents acting to maximize (expected) value, and under *full information*.[1] From a causal perspective, this approach is equivalent to assuming a graph in which all paths from e to y are blocked by x, r—which is akin to assuming no spurious pathways, and so handicaps the ability to avoid them.

Boundedly-rational users. We propose to model users as boundedly-rational decision-makers, under the key assertion that users' decisions take place under inherent *uncertainty*. Uncertainty plays a key role in how we, as humans, decide: our actions follow not only from what we know, but also from how we account for what we don't know. Nonetheless, and despite being central to most modern theories of decision making [25]—and despite being a primary reason for why users turn to online informational services like recommendation systems in the first place—explicit modeling of user-side uncertainty is currently rare within machine learning [37,2,38]; here we advocate for its use.

Our modeling approach acknowledges that users *know* some features are unobserved, and that this influences their actions. Here we demonstrate how this relates to robust learning through an illustrative example using a particular behavioral model, though as we will show, our approach applies more broadly. Consider a user shopping online for a vintage coat, and considering whether to buy a certain coat. The coat's description includes several intrinsic properties x (e.g., the coat's material), as well as certain platform-selected information r (e.g., a stylized photo of a vintage-looking coat). The user wants to make an informed decision, but knows some important information, $\bar{x}$, is missing (e.g.,

[1] For simplicity, here and throughout we consider deterministic valuations, although this is not necessary.

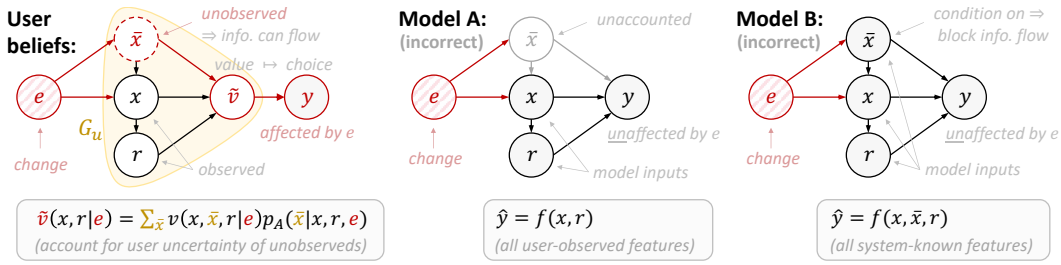

Figure 3: **(Left)** User causal beliefs. Integration of uncertainty in unobserved $\bar{x}$ results in a direct link $e \to y$ (note y is deterministic of $\tilde{v}$). This reveals a source of possible spuriousness, but also suggests how to treat it. **(Center)** A predictive model $f(x, r)$ using only observed features. Learning results in x, r compensating for e, and so f cannot account for change. **(Right)** A predictive model $f(x, \bar{x}, r)$ using all available features. Learning results in wrongly using variation in $\bar{x}$ to explain y.

the year in which the coat was manufactured). If she is concerned about buying a modern knockoff (rather than a truly vintage coat), how should she act? A common approach is to extend EUT to support uncertainty by modelling users as integrating subjective beliefs about unobserved variables, $p_u(\bar{x}|x, r, e)$, into a conditional estimate of value, $\tilde{v}_u(x, r|e)$, over which choices y are made:

$$\tilde{v}_u(x, r|e) = \sum_{\bar{x}} v_u(x, \bar{x}, r) p_u(\bar{x}|x, r, e), \qquad y = \mathbb{1}\{\tilde{v}_u(x, r|e) > 0\} \tag{1}$$

Here, $p_u(\bar{x}|x, r, e)$ describes a user's (probabilistic) belief regarding the conditional likelihood of each $\bar{x}$ (is the vintage-looking coat truly from the 60's?), and $v_u(x, \bar{x}, r)$ describes the item's value to the user *given* $\bar{x}$ (if the coat really is from the 60's—how much is it worth to me?). Importantly, note that uncertainty beliefs $p_u(\bar{x}|x, r, e)$ can be environment-specific (i.e., the degree of suspicion regarding knockoffs can vary across retailers). In turn, value estimates $\tilde{v}$ and choices y can also rely on e. For clarity, since y is a deterministic function of $\tilde{v}$, we will simply refer to y as a function of x, r, and e.

Causal user graphs. One interpretation of Eq. (1) is that users cope with uncertainty by employing *causal reasoning* [47], this aligning with a predominant approach in the cognitive sciences that views humans as acting based on 'mental causal models' [45]. Here we follow [47] and think of users as reasoning through personalized *user causal graphs*, denoted G_u. The structure of G_u expresses u's causal beliefs—namely which variables causally affect others—and its factors correspond to the conditional terms (p_u and v_u) in Eq. (1). A key modeling point is that users can vary in their causal perceptions; hence, different users may have different graphs that encode different conditional independencies, these inducing different simplifications of the conditional terms. For example, a user that believes movies with a five-star rating (r) are worthwhile regardless of their content (x) would have $v_u(x, \bar{x}, r)$ reduced to $v_u(\bar{x}, r)$, since $v \perp\!\!\!\perp x|r$; meanwhile, a user who, after reading a movie's description (x), is unaffected by its rating (r), would have $v_u(x, \bar{x})$ instead, since $v \perp\!\!\!\perp r|x$.

3.3 Towards robust learning

We are now ready to make the connection to robust learning. Recall that our goal is to learn a predictor f that is unaffected by spurious correlations, and that these can materialize through direct edges $e \to y$ (as in Figure 2). Continuing our illustrative example, assume that the causal beliefs of our boundedly-rational user (who chooses via Eq. (1)) are encoded by the graph in Figure 3. The graph does not have a direct edge $e \to y$; however, by accounting for uncertainty (i.e., choosing via $\tilde{v}$), the user behaves 'as if' there actually was a direct edge—since integrating over $\bar{x}$ 'removes' it from the indirect path $e \to \bar{x} \to y$. This support our main argument: by making decisions, users can *generate* spurious correlations in the data (here, via uncertainty). Figure 3 ('User model') illustrates this idea.

The above has two implications. First, it shows how conventional approaches can fail. For example, since users observe only x and r, one reasonable approach is to discard $\bar{x}$ and train a predictor $f_u(x, r; \theta)$ in hopes of mimicking user choice behavior (Fig. 3 ('Model A')). In graphical terms, this means learning 'as if' there is no edge $e \to y$. But the reliance of users on $\bar{x}$ for producing y (e.g., by integrating beliefs) means that, effectively, such an edge exists. The result of this is that f_u can learn to use x and r to compensate for the constant effect of e (and in particular, train-time instantiations e_k) on y. By definition, once e changes, the new (residual) effect on y is unaccounted for.

Conversely, the system may choose to learn using all available information, namely train $f_u(x, \bar{x}, r; \theta)$ (Fig. 3 ('Model B')). This make sense if the goal is in-distribution (ID) generalization; for out-of-distribution, This not only creates an illusion of separation between e and y, but also erroneously allows to use the variation in $\bar{x}$ to explain y (whereas the true y does not rely on specific instantiations of $\bar{x}$). As a result, the learned f_u will likely overfit to training distributions in $\mathcal{E}_{\text{train}}$.

Second, the awareness to how users account for uncertainty suggests a means to combat spuriousness. Eq. (1) shows that y depends on x, r, and e; hence, since our goal is to discourage the dependence of $\hat{y}$ on e, it follows that (i) functionally, f_u should depend only on x and r but (ii) f_u should be learned in a way that controls for (conditional) variation in e. In our example, this manifests in the role of $\bar{x}$: at *train-time* use $\bar{x}$ (perhaps indirectly) to learn a function that at *test-time* does not rely on it (c.f. Model B which uses $\bar{x}$ for both train and test, and Model A which does not use $\bar{x}$ at all). Since the precise way in which e relates to other variables is determined by the user graph G_u (which determines conditional independencies), knowledge of the graph should be useful in promoting invariance.

4 Learning With Causal User Models

Our approach to robust learning is based on regularized risk minimization, where regularization acts to discourage variation in predictions across environments [54,55]. Our learning objective is:

$$\underset{f \in F}{\text{argmin}}\, L(f; S) + \lambda R(f; S_1, \dots, S_K) \tag{2}$$

where F is the function class, L is the average loss w.r.t an empirical loss function (e.g., log-loss), and R is a data-dependent regularization term with coefficient λ. The role of R is to penalize f for violating certain statistical independencies; the question of *which* independencies should be targeted—and hence the precise form that R should have—can be answered by the underlying causal graph [54]. Knowing the full user graph (e.g. detailed causal relations between different features within x, such as whether the genre of a movie is a cause for its production quality) can certainly help , but relying on this (and at scale) is impractical. Luckily, as we show here, coarse information regarding the graph can be translated into necessary conditions for distributional robustness, and in §5 we will see that these can go a long way towards learning robust models in practice.

Note that by choosing to promote robustness through regularization, our approach becomes agnostic to the choice of function class F (although the graph may also be helpful in this[2]). We also need not commit to any specific behavioral choice model. This allows us to abstract away from the particular behavioral mechanism that generates spuriousness (e.g., integration of $\bar{x}$), and consider general relations between e and y (e.g., selection or common cause); we make use of this in our experiments.

Regularization schemes. We focus on two methods for promoting statistical independence: MMD [22], which we present here; and CORAL [52], which we describe in Appendix C (we use both in our experiments). The MMD regularizer applies to models f that can be expressed as a predictor h applied to a (learned) representation mapping ϕ, i.e., $f = h \circ \phi$ (note h can be vacuous). MMD works by encouraging the (empirical) distribution of representations for each environment e_k to be indistinguishable from all others; this is one way to express the independence test for $\hat{y}$ and e [54]. In our case, for a single e_k, MMD is instantiated as:

$$\text{MMD}(\Phi_k, \Phi_{-k}), \quad \text{where} \quad \Phi_k = \{\phi(x) : x \in S_k\},\ \Phi_{-k} = \{\phi(x) : x \in S \setminus S_k\}. \tag{3}$$

As we show next, the precise way in which MMD is used for regularization depends on the graph.

4.1 User graph classes: causal vs. anti-causal

Following our example in Fig.1a, consider users of two types: a 'causal' user $u_{\rightarrow y}$ that believes value is an *effect* of an item's description (i.e., $D^e(x, r, y \mid u = u_{\rightarrow y})$ is entailed by the graph $x, r \rightarrow y$ for each $e \in \mathcal{E}$), and an 'anti-causal' user $u_{\leftarrow y}$ that believes the item's value *causes* its description (i.e., $D^e(x, r, y \mid u = u_{\leftarrow y})$ is entailed by $x, r \leftarrow y$ respectively). Our next result shows that: (i) $u_{\rightarrow y}$ and $u_{\leftarrow y}$ require *different* regularization schemes; but (ii) that the appropriate scheme is fully determined by their type—*irrespective* of any other properties of their graphs. Thus, from a learning perspective, it suffices to know which of two classes a user belongs to: causal, or anti-causal.

[2] E.g., if we aim to learn parameterized predictors on the basis of Eq. (1), graphs can help discard dependencies.

Proposition 1. *Let f be a CI model and assume y and e are confounded (e.g., $e \to y$ exists), then:*

(1) $f_{u_{\to y}}$ must satisfy $P_{D^e}\left(f_{u_{\to y}}(x,r)\right) = P_{D^{e'}}\left(f_{u_{\to y}}(x,r)\right) \;\; \forall e, e' \in \mathcal{E}$

(2) $f_{u_{\leftarrow y}}$ must satisfy $P_{D^e}\left(f_{u_{\leftarrow y}}(x,r) \mid y\right) = P_{D^{e'}}\left(f_{u_{\leftarrow y}}(x,r) \mid y\right) \;\; \forall e, e' \in \mathcal{E},\; y \in \{0,1\}$

On the other hand, $f_{u_{\to y}}$ need not necessarily satisfy (2), and $f_{u_{\leftarrow y}}$ need not necessarily satisfy (1).

If we fail to enforce these constraints during learning, then we will not learn a CI classifier. On the other hand, enforcing unnecessary constraints (e.g., requiring both conditions hold for $f_{u_{\to y}}$ and $f_{u_{\leftarrow y}}$) restricts our hypothesis class and hence limits performance. The proof follows directly from [54] (under technical assumptions; see Appendix A). The distinction between causal and anti-causal is fundamental in causality [41]; for our purposes, it prescribes the appropriate regularization.

Corollary 1. *For any user u, to encourage $f_u(x,r)$ to be invariant to changes in e, set:*

$$R(f;S) = \begin{cases} \sum_k \mathrm{MMD}(\Phi_{k,u}, \Phi_{-k,u}) & u \text{ is causal} \quad \textit{(marginal MMD)} \\ \sum_y \sum_k \mathrm{MMD}(\Phi^{(y)}_{k,u}, \Phi^{(y)}_{-k,u}) & u \text{ is anti-causal} \quad \textit{(conditional MMD)} \end{cases} \tag{4}$$

where $\Phi_{k,u}, \Phi^{(y)}_k$ includes the subset of examples with user u and label y, respectively.

When learning over multiple users (as in Eq. (2)), the operational conclusion is that all users of the same class—regardless of their specific graphs—should be regularized in the same manner, and according to Eq. (4). Determining a user's class is simpler than full graph inference, as it requires only the directionality of a subset of edges. This can be done using focused interventions (e.g., A/B testing), or for observational data, using simple conditional independence tests (e.g., [48,21]) [42].

4.2 User graph subclasses: inter-feature relations

Consider now two users that are of the same class (i.e., causal or anti-causal), but perceive differently the causal relations between x and r: a *believer*, $u_{x\to r}$, who believes recommendations follow from the item's attributes; and a *skeptic*, $u_{x\leftarrow r}$, who presumes that the system reveals item attributes to match a desired recommendation (see Fig.1b). Our main result shows that even if both users share the same objective preferences and hence exhibit the same choice patterns—to be *optimally* invariant, each user may require her own, independently-trained model (though with the same regularization).

Proposition 2. *Let $u_{x\to r}, u_{x\leftarrow r}$ be two users of the same class (i.e., causal or anti-causal) but of a different subclass (i.e., believer and skeptic, respectively). Even if there is a single predictor f which is optimal for the pooled distribution D_{train}, each user can have a different optimal CI predictor.*

Proof is in Appendix A. Prop. 2 can be interpreted as follows: Take some u, and 'counterfactually' invert the edges between x and r. In some cases, this will have no effect on u's behavior under $\mathcal{E}_{\text{train}}$, and so any f that is optimal in one case will also be optimal in the other. Nonetheless, for optimality to carry over to *other* environments—different predictors may be needed. This is since each causal structure implies a different interventional distribution, and hence a different set of CI predictors: e.g., in $G_{x\leftarrow r}$, the v-structure $e \to x \leftarrow r$ suggests that an invariant predictor may depend on r, yet in $G_{x\to r}$ it cannot. If the sets of CI predictors do not intersect, then necessarily there is no single optimal model.

The practical take-away is that even if two different users exhibit similar observed behavioral patterns (e.g., differences in their graphs are not expressed in the data), whether they are skeptics or believers has implications for robust learning; Prop. 2 considers an extreme case. Luckily, for data with mixed subclasses, having multiple training environments enables us to nonetheless learn invariant predictors, e.g., by partitioning the data by user subclass and learning a different model for each subclass (with regularization determined by class). In §5.3, we empirically evaluate this approach.

5 Experiments and Results

We present three experiments: two targeting user classes (*causal* or *anti-causal*) and using real data, and one targeting user subclasses (*believers* and *skeptics*) and using synthetic data. Appendix B includes further details on model architectures, training procedures, and data generation.

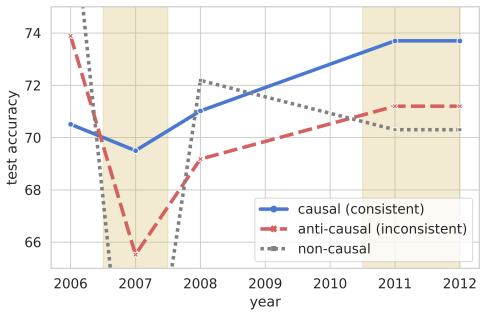

Figure 4: ***RecBeer* Results**. For each year, models are trained on past data (starting 2002), and predict on the following year. The *causal* training scheme, consistent with the user class, outperforms other methods when beer-type fashions (e) changes. Periods with substantial change are highlighted in tan.

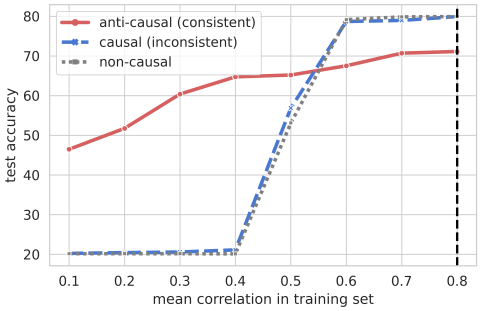

Figure 5: ***RecFashion* Results**. Environments vary in the correlation between item colors and user choices. The *anti-causal* regularization scheme, consistent with the user class, outperforms methods when test-time deviates from train-time correlation (=0.8). When correlations flip (< 0.5), other methods crash.

5.1 Learning with *causal* users: text-based beer recommendation

Data. We use *RateBeer*, a dataset of beer reviews with over 3M entries and spanning $\sim$ 10 years [32]. We use the data to generate beer features x (e.g., popularity, average rating) and r (e.g., textual review embeddings) and user features u (e.g., average rating, word counts). Given a sample (u, x, r), our goal is to predict a (binarized) rating y. Here we focus on *causal* users, and so would like labels y to expresses causal user beliefs. The challenge is that our observational data is not necessarily such. To simulate causal user behavior, we rely on the observation that $x, r \rightarrow y$ means "changes in x, r affect y", and for each u create an individualized empirical distribution of 'counterfactual' samples (x', r', y') that approximate the entire intervention space (i.e., all counterfactual outcomes y' under possible interventions $(x, r) \mapsto (x', r')$). Training data is then generated by sampling from this space.

We consider each year as an environment e, with each e inducing a distribution over (u, x, r). We implement spuriousness via selection: Each e entails different fashionable 'tastes' in beer, expressed as a different weighting over the possible beer types (e.g., lager, ale, porter). Labels are then made to correlate with tastes in a certain temporal pattern. This serves as a mechanism for spurious correlation.

Results. Fig. 4 compares the performance over time of three training procedures that differ only in the type of regularization applied: *causal*, *anti-causal*, and *non-causal*. Our data includes behavior generated by causal-class users; results demonstrate the clear benefit of using a behaviorally-consistent regularization scheme (here, causal). Note the causal approach is not optimal in 2006 and 2008; this is since correlations in $e \leftrightarrow y$ are set to make these years similar to the training data. However, in the face of significant shifts in taste, other approaches collapse, while the causal approach remains stable.

5.2 Learning with *anti-causal* users: clothing-style recommendation

Data. We use the *fashion product images* dataset[3], which includes includes 44.4k fashion items described by images, attributes, and text. Here we focus on *anti-causal* users, and generate data in a way similar to §5.1, but using an anti-causal intervention space. In this experiment we let user choices $y \in \{0, 1\}$ depend on an item's image and color, which can be either red or green; in this way, x is the item's grayscale image, and r its hue (which we control).[4] Here we consider environments e that induce varying degrees of spurious correlations between color and user choices, $P(y = 1|\texttt{red}) = P(y = 0|\texttt{green}) = p_e$. For the test set we use $p_e = 0.8$, and experiment with training data that gradually deviate from this relation, i.e., having $p_{e'} \in [0.1, 0.8]$.

Results. Fig. 5 shows that consistent regularization (here, anti-causal) outperforms other alternatives whenever correlations deviate from those observed in training. Once correlations flip (< 0.5), both *causal* and *non-causal* approaches fail catastrophically; the *anti-causal* approach remains robust.

[3] https://www.kaggle.com/paramaggarwal/fashion-product-images-dataset

[4] Note this means users observe as input a 'fusion' of x and r (i.e., a colored image), and not each individually.

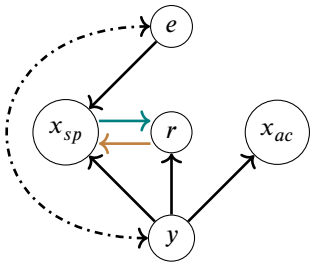

Figure 6: Data-generating process for the user subclass experiment (synthetic). Here, x factorizes into an *anti-causal* component x_{ac}, and a spurious component x_{sp} linked with r. Spuriousness results from selection bias between y and e.

Table 1: Accuracy for the user subclass experiment. Rows show train conditions: with and without regularization, and which users are included in the training set. Columns show test conditions: ID/OOD, and user type. Best results for each train condition (rows) are highlighted in bold.

Reg.	Users@train	Accuracy (ID / OOD) *skeptic*	*believer*
$\lambda = 0$	*skeptic*	**78.0** / 50.0	**89.8** / 75.1
	believer	**78.0** / 50.0	**89.8** / 75.1
	both	**78.0** / 50.0	**89.8** / 75.1
$\lambda > 0$	*skeptic*	71.1 / **75.6**	74.67 / 75.5
	believer	69.8 / 52.5	88.5 / **85.2**
	both	70.03 / 64.57	78.88 / 78.13

5.3 Learning with multiple user subclasses

Our final experiment studies learning with users of of the same-class (here, *anti-causal*) but different sub-classes: *skeptics* or *believers*. Our analysis in §4.2 suggests that each user sub-class may have a different optimal predictor; here we investigate this empirically on synthetic data.

Data. The data-generating process is as follows (see Fig. 5.2). We use three environments: e_1, e_2 at train, and e_3 at test, and implement a selection mechanism (dashed line) that causes differences in $p(y|e_i)$ across e_i. Since we focus on anti-causal users, features x, r are determined by e, y. We use three binary features: x_{sp} ('spurious'), x_{ac} ('anti-causal'), and r. These are designed so that an f which uses x_{ac} alone obtains 0.75 accuracy, but using also x_{sp} improves *in-distribution* (ID) accuracy slightly to 0.78, and so the optimal ID predictor for both user subclasses is of the form $f^*(x_{ac}, x_{sp})$. However, relying on x_{sp} causes *out-of-distribution* (OOD) performance to deteriorate considerably; thus, robust models should not learn to discard x_{sp}. The role of r is to distinguish between user subclasses: The skeptic does not need r since, for her, it is fully determined by x_{sp}; the optimal invariant predictor is hence $f_{x \to r}(x_{ac})$. Meanwhile, the believer, due to the v-structure $r \to x_{sp} \leftarrow e$, can benefit in-distribution by using both r and x_{sp}; here, the optimal invariant predictor is $f_{x \leftarrow r}(x_{ac}, r)$.

Results. Table 1 shows ID and OOD performance for each user subclass (columns), for learning with and without regularization (rows). Since all users are anti-causal, we use anti-causal (i.e., conditional) regularization. We compare learning a separate predictor for each user type (rows '*skeptic*' and '*believer*') and learning a single predictor over all users jointly ('both'). Results show that without regularization ($\lambda = 0$), ID performance is good, but the learned predictor fails OOD—drastically for skeptic users (note all rows are the same since both user types share the same ID-optimal f^*). In contrast, when regularization is applied ($\lambda > 0$), learning an independent predictor for each user subclass performs well OOD (for both subclasses), indicating robustness to changing environments; note that ID performance is also mostly maintained. Meanwhile, learning on the entire dataset (i.e., including both user types) does provide some robustness—but is suboptimal both ID and OOD.

5.4 Learning with mixed sub-populations

Our previous experiment considered a setting in which the learner has exact information regarding each user's sub-type, and so can correctly partition the population in a way that is optimal in regards to Prop. 2. However, such precise knowledge may not be available in practice, or may be too costly or difficult to infer. In this section we experiment in a setting where the learner has only coarse information (or general beliefs) about user (sub-)types. Our results suggests that following the practical conclusions of Prop. 2—namely partitioning the population of users based on (estimated) types and learning a different predictive model for each—can be beneficial even when based only on a reasonable guess.

Data. We use the setting of Sec.5.3 with a population of anti-causal users, composed of two sub-populations of skeptics and believers. We then simulate a setting where the learner has imprecise information about user types by adding noise: we move an α-fraction of each subpopulation into the other, this creating two mixed sub-populations. We then run a series of experiments, where a

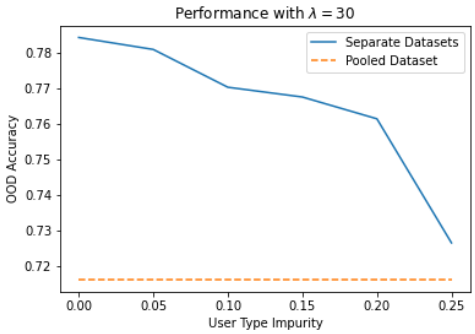

Figure 7: Performance of learning with conditional MMD under datasets with mixed Believers and Skeptics. X-axis denotes the fraction α_{flip} that is switched between the subpopulations and Y values show the performance in test environments.

robust model is trained using conditional MMD regularization, with increasing levels of 'impurity', $\alpha \in [0, 0.25]$. Here, $\alpha = 0$ represents perfect information, and in $\alpha = 0.25$ we have large minority groups (25%) in each set.

Results. Fig. 7 presents OOD performance for the robust model (solid line), in comparison to a naïve model trained on the pooled dataset (dashed line). In line with our earlier results, for $\alpha = 0$, the robust model achieves significantly higher accuracy on the test environment. Additional, as α increases, the robust model preserves its advantage, with accuracy degrading gracefully; for $\alpha = 0.25$, the robust model still outperforms the pooled baseline. Thus, our results show that even under a considerable amount of noise (or, alternatively, with imprecise sub-type information), it is still beneficial to learn distinct models for each subpopulation.

6 Discussion

Humans beings perceive the world causally; our paper argues that to cope with a world that *changes*, learning must take into account how humans believe these changes take effect. We identify one key reason: in making decisions under uncertainty, users can *cause* spurious correlations to appear in the data. Towards this, we propose to employ tools from invariant causal learning, but in a way that is tailored to how humans make decisions, this drawing on economic models of bounded-rationality. Our approach relies on regularization for achieving invariance, with our main point being that *how* and *what* to regularize can be derived from users' causal graphs. Although we have argued that even partial graph information can be helpful—even this form of knowledge is not straightforward to obtain (notably at test-time), and may require experimentation. Nonetheless, and in hopes of spurring further interest, we view our work as taking one step towards establishing a disciplined causal perspective on the interaction between recommending systems and the decision-making users they aim to serve.

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Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes] Limitations that we found most significant are discussed in 6
   (c) Did you discuss any potential negative societal impacts of your work? [No] The work does not treat a specific task where we see an immediate risk for negative societal impact. Though the methods described in this paper might be used by practitioners, and we suggest doing so with care since the suggested methods need to be studied further in controlled settings before being used in such domains.
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes] The paper conforms with the provided guidelines.
2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [N/A]
   (b) Did you include complete proofs of all theoretical results? [N/A]
3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes] Code and Data for reproducing all of our results are submitted as part of the supplementary material.
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes] See Section 5 and Supplementary material
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [Yes] All results are averaged across 5 runs
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes] See supplementary material.
4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
   (a) If your work uses existing assets, did you cite the creators? [Yes] See Section 5
   (b) Did you mention the license of the assets? [Yes] See supplementary material
   (c) Did you include any new assets either in the supplemental material or as a URL? [Yes]
   (d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? [No] All assets we use are allowed for public use for the purposes of scientific research.
   (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [No] The data we use is taken from publicly available datasets, where all personally identifiable information have been removed.
5. If you used crowdsourcing or conducted research with human subjects...
   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A] We did not conduct research with human subjects
   (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A]
   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A]