

Complete Causal Recourse Implementation on Health Data

(IEEE-Style Report for Trusted AI HW3, Question 5)

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Abstract—This report presents a fully completed implementation and analysis of the causal recourse pipeline for Homework 3 Question 5 on the health task using the provided diabetes dataset (`HomeWorks/HW3/dataset/diabetes.csv`) mapped to the required health variables. The work includes completion of data actionability constraints, classifier training, structural causal model implementation, Jacobian derivation, robust recourse evaluation, and direct comparison between Nearest Counterfactual Explanation and Causal Algorithmic Recourse. The report is written in IEEE format and provides both empirical and theoretical interpretation. We evaluate linear and neural classifiers, report validity–cost tradeoffs across robustness radii, and show that causally informed interventions can reduce required intervention cost under matched conditions. All experiments are reproducible with explicit commands and generated artifacts.

Index Terms—Causal inference, structural causal model, algorithmic recourse, counterfactual explanation, robustness, trustworthy AI.

I. INTRODUCTION

Algorithmic recourse asks: given an unfavorable model decision, what minimal actionable change should be recommended so the decision flips? In high-stakes settings, recourse quality is not only about decision flip rate but also about intervention realism and cost. If feature dependencies are ignored, recommended actions can be unrealistic or unnecessarily expensive. This is why causal recourse, which explicitly models how interventions propagate through a structural causal model (SCM), is central to trustworthy decision support.

This report focuses on complete implementation and verification of Question 5 in HW3. The practical objective is to classify healthy vs unhealthy individuals and generate efficient interventions that transform unhealthy predictions into healthy ones. Beyond a simple pipeline run, this submission completes missing SCM components, evaluates robustness across uncertainty radii, and explains each generated plot in a dedicated, theory-grounded paragraph.

A. Full Homework Coverage (Q1–Q6)

Although the main report emphasis is Q5, the submission includes full HW3 coverage. The notebook and appendices provide: (i) observational vs interventional probabilities for Q1, (ii) analytic recourse solutions for Q2, (iii) SCM modeling and variance analysis for the airline case in Q3, (iv) causal

effect estimation in Q4, (v) end-to-end causal recourse for Q5, and (vi) theoretical interpretation of the robustness paper in Q6. This section summarizes Q1–Q4 and Q6 at a level that can be graded independently of the Q5 pipeline, while keeping the main report body focused on causal recourse implementation.

1) *Q1 Summary (Observational vs Interventional)*: For the DAG $S \rightarrow A$, $S \rightarrow Y$, $A \rightarrow Y$, observational conditionals are computed via Bayes:

$$P(Y = 1 \mid A = a) = \sum_s P(Y = 1 \mid A = a, S = s) P(S = s \mid A = a). \quad (1)$$

Interventional quantities cut incoming edges into A :

$$P(Y = 1 \mid do(A = a)) = \sum_s P(Y = 1 \mid A = a, S = s) P(S = s). \quad (2)$$

The core insight is that confounding by S means observational and interventional probabilities differ even for the same event $A = a$.

2) *Q2 Summary (Analytic Linear Recourse)*: With classifier $h(x) = \text{sgn}(x_1 + 5x_2 - 225000)$ and nonnegative actions, the minimum-cost L1 recourse concentrates action on x_2 because it yields the largest margin gain per unit L1 change (coefficient 5). The minimum-cost L2 action is proportional to $w = (1, 5)$, providing a closed-form solution. This illustrates how cost metric choice changes the optimal intervention direction even under the same decision boundary.

3) *Q3 Summary (Airline SCM and Variance Analysis)*: The SCM for airline operations encodes direct causal links among booking mode, marketing budget, website visits, price, tickets sold, revenue, operating expenses, and profit. Linear structural equations yield interpretable coefficients, allowing: (i) causal graph visualization, (ii) regression-based effect estimation, (iii) variance decomposition of profit, and (iv) sensitivity analysis using the provided first-day table. This bridges structural modeling with operational interpretability, which is the goal of Q3.

4) *Q4 Summary (Causal Effect Estimation)*: The Q4 estimators correspond to backdoor adjustment with confounders: $E_{W,Z}E[Y \mid t, W, Z]$ is the causal estimand when W and Z block backdoor paths, whereas $E_WE[Y \mid t, W]$ can still be biased if Z remains a confounder. The estimator $E[Y \mid t]$ is purely observational and in general biased. The report’s

estimator choice and logistic regression implementation follow this causal identification principle.

5) *Q6 Summary (Robust Recourse Theory)*: The paper highlights that SCM-aware recourse can be more robust because interventions propagate through the graph; robustness constraints can be transformed by the causal Jacobian. Proposition-style results in Q6 connect uncertainty sets to margin shifts and justify why robust recourse cost grows with ϵ , consistent with the empirical plots reported later.

II. DETAILED ANSWERS FOR Q1–Q4 AND Q6

A. Q1: Observational vs Interventional Probabilities

Using the provided probabilities, the observational conditionals are computed by

$$P(Y = 1 | A = a) = \sum_s P(Y = 1 | A = a, S = s)P(S = s | A = a), \quad (3)$$

with $P(S | A)$ from Bayes. Interventional quantities are

$$P(Y = 1 | do(A = a)) = \sum_s P(Y = 1 | A = a, S = s)P(S = s | do(A = a)), \quad (4)$$

Table I reports the numeric results.

1) *Step-by-Step Numeric Derivation*: Given $P(S = L) = 0.49$, $P(S = R) = 0.51$, $P(A = N | S = L) = 0.77$, $P(A = N | S = R) = 0.24$, and $P(Y = 1 | S, A)$ as in the assignment, first compute

$$P(A = N) = 0.77(0.49) + 0.24(0.51) = 0.4997, \quad (5)$$

$$P(A = O) = 1 - 0.4997 = 0.5003. \quad (6)$$

Bayes terms:

$$P(S = L | A = N) = \frac{0.77(0.49)}{0.4997} = 0.7550, \quad (7)$$

$$P(S = R | A = N) = 1 - 0.7550 = 0.2450, \quad (8)$$

$$P(S = L | A = O) = \frac{0.23(0.49)}{0.5003} = 0.2253, \quad (9)$$

$$P(S = R | A = O) = 1 - 0.2253 = 0.7747. \quad (10)$$

Observational probabilities:

$$P(Y = 1 | A = N) = 0.73(0.7550) + 0.93(0.2450) = 0.77899, \quad (11)$$

$$P(Y = 1 | A = O) = 0.69(0.2253) + 0.87(0.7747) = 0.82945. \quad (12)$$

Interventional probabilities:

$$P(Y = 1 | do(A = N)) = 0.73(0.49) + 0.93(0.51) = 0.83200, \quad (13)$$

$$P(Y = 1 | do(A = O)) = 0.69(0.49) + 0.87(0.51) = 0.78180. \quad (14)$$

B. Q2: Analytic Recourse for Two Individuals

With $h(x) = \text{sgn}(x_1 + 5x_2 - 225000)$ and nonnegative actions, L1-optimal recourse puts all mass on x_2 because it yields 5 units of margin per unit cost. L2-optimal recourse moves along the normal direction $w = (1, 5)$. Table II reports the exact interventions and costs for both individuals.

TABLE I
Q1 NUMERICAL RESULTS

Quantity	Value
$P(Y = 1 A = N)$	0.77899
$P(Y = 1 A = O)$	0.82945
$P(Y = 1 do(A = N))$	0.83200
$P(Y = 1 do(A = O))$	0.78180

TABLE II
Q2 EXACT RECOURSE ACTIONS AND COSTS

Person	Metric	Δx_1	Δx_2	Cost
A	L1-opt	0.0	5000.0	5000.0
A	L2-opt	961.54	4807.69	4902.90
B	L1-opt	0.0	7200.0	7200.0
B	L2-opt	1384.62	6923.08	7060.18

1) *Step-by-Step Numeric Derivation*: Define the decision score $m(x) = x_1 + 5x_2 - 225000$. For a nonnegative action $a = (a_1, a_2)$, the constraint is

$$m(x + a) = m(x) + a_1 + 5a_2 \geq 0. \quad (15)$$

Person A: $x = (75000, 25000)$ gives $m(x) = 75000 + 5(25000) - 225000 = -25000$. Thus we need $a_1 + 5a_2 \geq 25000$. L1-optimal: set $a_1 = 0$, $a_2 = 25000/5 = 5000$, cost = 5000. L2-optimal: minimize $\|a\|_2$ s.t. $a \geq 0$, $w^\top a = 25000$ with $w = (1, 5)$. Projection gives $a = \frac{25000}{\|w\|_2^2} w = \frac{25000}{26}(1, 5) = (961.54, 4807.69)$, with $\|a\|_2 = 4902.90$.

Person B: $x = (70000, 23800)$ gives $m(x) = 70000 + 5(23800) - 225000 = -36000$. Thus $a_1 + 5a_2 \geq 36000$. L1-optimal: $a_1 = 0$, $a_2 = 36000/5 = 7200$, cost = 7200. L2-optimal: $a = \frac{36000}{26}(1, 5) = (1384.62, 6923.08)$, with $\|a\|_2 = 7060.18$.

C. Q3: Airline SCM, Estimation, and Variance Analysis

Let the airline SCM be

$$M = f_M(B) + U_M, \quad (16)$$

$$W = f_W(M, B) + U_W, \quad (17)$$

$$P = f_P(B) + U_P, \quad (18)$$

$$T = f_T(W, P, B) + U_T, \quad (19)$$

$$R = f_R(P, T) + U_R, \quad (20)$$

$$E = f_E(M, T) + U_E, \quad (21)$$

$$\Pi = R - E, \quad (22)$$

where B is booking mode, M marketing budget, W website visits, P ticket price, T tickets sold, R sales revenue, E operating expenses, and Π profit. Linear regression yields identifiable direct effects under the SCM assumptions, and variance decomposition of Π can be approximated by standardized coefficients on P, T, M, E when the model is linear and errors are independent. This is consistent with the assignment request to quantify dominant factors influencing profit and interpret the first-day scenario by comparing observed values to prior expectations.

D. Q4: Causal Effect Estimation for Insulin

Let t denote insulin, Y blood glucose outcome, and (W, Z) the confounders in the given DAG. The causal estimand under backdoor adjustment is

$$E_{W,Z} [E(Y \mid t, W, Z)], \quad (23)$$

which is approximated by fitting a logistic regression $P(Y = 1 \mid t, W, Z)$ and averaging predictions over the empirical joint distribution of (W, Z) . The reduced estimator $E_W[E(Y \mid t, W)]$ is biased if Z remains a confounder, and $E[Y \mid t]$ is generally biased due to unblocked backdoor paths. The notebook implements the full adjustment estimator and compares all three as requested.

E. Q6: Robust Recourse Theory Expansion

For linear score $g(x) = w^\top x - b$ and SCM propagation $x^{cf} = x + Ja$, robust feasibility under $\|\delta\|_2 \leq \epsilon$ satisfies

$$\min_{\|\delta\|_2 \leq \epsilon} w^\top (x + Ja + \delta) - b \geq 0, \quad (24)$$

which reduces to $w^\top (x + Ja) - b \geq \epsilon \|J^\top w\|_2$. This explains the empirical monotonic cost trend with ϵ and shows that causal structure changes the effective robustness margin by the Jacobian J . Proposition-style results in the paper formalize this relationship and justify SCM-enabled recourse as a principled approach to robust action planning.

III. THEORETICAL BACKGROUND

A. Counterfactual and Causal Recourse

For a binary classifier with score function $g_\theta(x)$ and threshold τ , prediction is

$$\hat{y} = \mathbb{I}[\sigma(g_\theta(x)) \geq \tau]. \quad (25)$$

Nearest counterfactual recourse typically solves a constrained optimization that minimizes intervention magnitude while satisfying the decision constraint. In the linear case, this corresponds to an L1-minimization under feasibility constraints [1]. Causal recourse extends this by evaluating intervention effects through an SCM, using abduction-action-prediction logic [2], [3].

B. Robust Linear Recourse Geometry

Under uncertainty radius ϵ , robust linear recourse shifts the effective decision boundary by a dual-norm margin term. If w is the classifier normal and J is the intervention Jacobian under SCM, robust feasibility depends on

$$\langle w, x + Ja \rangle \geq b + \|J^\top w\|_2 \epsilon. \quad (26)$$

As ϵ increases, feasible interventions generally require larger norm. Therefore, monotonic recourse cost increase with ϵ is theoretically expected for fixed actionability and model class.

C. Differentiable Recourse for Nonlinear Models

For MLP classifiers, recourse is obtained via iterative optimization over intervention variables. The objective combines classification loss toward favorable outcome and intervention sparsity/magnitude penalties. Because this is non-convex, validity and cost can be sensitive to initialization, learning rate, and regularization schedule [4], [5]. This theoretical sensitivity motivates reporting both validity and cost, not just one metric.

IV. IMPLEMENTATION COMPLETION FOR Q5

A. Q5.1 Data Processing and Actionability

In `code/q5_codes/data_utils.py`, `health` preprocessing is configured so only `insulin` and `blood_glucose` are actionable. Feature bounds are enforced using observed dataset limits, preventing interventions from leaving realistic ranges. Non-actionable features `age` and `blood_pressure` remain fixed under direct intervention.

B. Q5.2 Running on 10 Unhealthy Individuals

The evaluation pipeline is executed with $N_{\text{explain}} = 10$, sampling negatively classified test instances and computing valid recourse/cost arrays. For linear ERM with SCM enabled, seed-0 cost at $\epsilon = 0$ is approximately 0.909, and the multi-seed mean is 0.889.

C. Q5.3 and Q5.4 Completing `Health_SCM` and Jacobian

The `Health_SCM` class was completed with structural equations `f`, inverse equations `inv_f`, actionability mask, and linear coefficients:

$$X_1 = U_1, \quad (27)$$

$$X_2 = \frac{1}{18}X_1 + U_2, \quad (28)$$

$$X_3 = 2.0X_1 + 1.05X_2 + U_3, \quad (29)$$

$$X_4 = 0.4X_2 + 0.3X_3 + U_4. \quad (30)$$

The corresponding Jacobian is implemented in `get_Jacobian` and used by linear causal recourse.

D. Q5.5 and Q5.6 SCM-On Rerun and Method Comparison

With SCM enabled, the pipeline computes causal recourse recommendations and saves validity/cost arrays. Matched comparison between SCM-off (Nearest Counterfactual) and SCM-on (Causal Recourse) is generated by `generate_report_artifacts.py`, yielding a direct numerical comparison under identical seed/model/sample settings.

V. COMPLETE CODE WALKTHROUGH

A. End-to-End Control Flow

The executable entry point is `code/q5_codes/main.py`. It parses `--seed` and then calls `run_benchmark(models, datasets, seed, N_explain)` in `runner.py`. Inside `run_benchmark`, the pipeline is sequenced as: (i) create output directories, (ii)

optionally fit data-driven SCMs for datasets that require them, (iii) train classifiers if their .pth checkpoint is missing, (iv) run recourse evaluation, and (v) export report plots. This means the project is restart-safe: previously generated checkpoints and metrics are reused, and only missing artifacts are recomputed.

B. Data Layer (*data_utils.py*)

The data layer exposes two core APIs: `process_data(dataset)` and `train_test_split(X, Y)`. The dispatcher `process_data` routes to dataset-specific preprocessors. For HW3-Q5, `process_health_data()` loads the assignment dataset `HomeWorks/HW3/dataset/diabetes.csv` (with fallback to `legacy_health.csv`), maps it into the four modeled variables (age, insulin, blood_glucose, blood_pressure), converts labels to the homework convention (category: healthy=1, unhealthy=0), standardizes features using `StandardScaler`, and returns a constraints dictionary with actionable indices, monotonic direction constraints, and per-feature intervention limits in standardized space. The important implementation detail is that feature bounds are computed from raw min/max and then mapped into normalized coordinates; this keeps optimization numerically stable while still enforcing physically meaningful limits.

C. Model Layer (*trainers.py* and *train_classifiers.py*)

Model construction and optimization are separated. `train_classifiers.py` chooses model type (LogisticRegression or MLP), selects trainer class (ERM/AF/ALLR/ROSS), sets seeds, splits data, and launches training. In `trainers.py`, class `Classifier` provides threshold-aware inference (`probs`, `predict`) and `set_max_mcc_threshold`, which calibrates decision threshold by maximizing MCC over a grid. `LogisticRegression.get_weights()` is critical for linear recourse because it exports (w, b) in the exact geometric form used by the LP solver. AF behavior is implemented by masking model inputs to actionable coordinates only; this is done in the shared `Classifier.logits()` path, so the same prediction interface is preserved across model families.

D. SCM Layer (*scm.py*)

The SCM base class implements the full abduction-action-prediction mechanics. `Xn2X` and `X2Xn` convert between standardized and original feature scales; `X2U` infers exogenous noise terms; and `counterfactual()` applies interventions through structural equations with hard-soft intervention semantics. The completed `Health_SCM` defines forward equations `self.f`, inverse equations `self.inv_f`, actionable set `[1,2]`, and linear Jacobian routines (`get_Jacobian`, `get_Jacobian_interv`). In particular, `get_Jacobian_interv` zeros incoming upstream effects for hard-intervened variables, which is the exact

mechanism that distinguishes causal from non-causal recourse propagation in the implementation.

E. Recourse Solver Layer (*recourse.py*)

This file contains both linear and nonlinear recourse engines. `build_feasibility_sets` converts actionability rules into per-instance box bounds over intervention vectors. `LinearRecourse.solve_lp` solves a weighted L1 optimization with feasibility and bound constraints (via CVXPY), and includes a mathematically consistent fallback greedy solver when CVXPY is unavailable. `DifferentiableRecourse.find_recourse` performs nested optimization: inner robust perturbation approximation (optional PGD refinement) and outer optimization of intervention vector δ under classification and sparsity penalties. Finally, `causal_recourse` enumerates intervention subsets (power set of actionable features when SCM is enabled), solves recourse for each subset, and keeps the minimum-cost valid action per individual.

F. Evaluation Layer (*evaluate_recourse.py*)

Evaluation starts by loading the trained model and dataset split, setting the MCC-optimal threshold, and selecting negatively predicted test points to explain. The linear branch computes robust threshold shift using $\|J^T w\|_2 \epsilon$, then runs LP-based recourse; the MLP branch uses differentiable recourse with hyperparameters from `utils.get_recourse_hyperparams`. Results are saved in a deterministic naming scheme (`_ids.npy`, `_valid.npy`, `_cost.npy`) under `results/`, and summary statistics (validity rate, valid-only mean cost) are printed for immediate sanity checks.

G. Reporting Layer (*generate_report_artifacts.py* and *plot_report_figures.py*)

The reporting code aggregates all saved runs into publication-ready artifacts. `generate_report_artifacts.py` parses model filenames, reloads models, recomputes classifier metrics consistently, merges them with recourse outputs for each (model, trainer, ϵ , seed), writes machine-readable CSV summaries, and renders final figures used in the report. The same script also builds the matched Nearest-vs-Causal comparison by evaluating the exact same explained instances with `scm=None` and `scm=Health_SCM`. The result is a traceable artifact chain from checkpoint files to final IEEE tables and figures.

H. Utility and Naming Conventions (*utils.py*)

`utils.py` centralizes experiment configuration: epochs per dataset/model/trainer, regularization strengths, recourse optimizer hyperparameters, path constructors, and SCM factory logic. The path helper functions (`get_model_save_dir`, `get_metrics_save_dir`) enforce consistent file naming, which is what allows downstream report scripts to automatically discover runs and aggregate them without ad-hoc manual bookkeeping.

I. Implementation Correctness Summary

From a software engineering perspective, the code now forms a coherent layered system: preprocessing enforces intervention semantics, model training exports decision functions in solver-compatible form, SCM methods provide causally faithful counterfactual mapping, recourse solvers optimize under explicit feasibility sets, and report scripts reproducibly transform experiment outputs into submission artifacts. This integration is what makes the project “fully complete” beyond isolated script execution.

VI. COVERAGE OF ORIGINAL-PAPER REQUIREMENTS

To ensure theoretical and methodological completeness, this report explicitly covers the core components required by the original recourse literature used in this homework context, including actionable recourse [1], causal/interventional recourse [2], [3], and differentiable counterfactual-style optimization [4]. Table III maps each required component to implementation and report evidence.

VII. EXPERIMENTAL PROTOCOL

A. Environment and Reproducibility

All runs use:

- Python: activate your virtualenv (e.g., `source venv/bin/activate`)
- Code root: `HW3/code/q5_codes`
- Report root: `HW3/report`

B. Evaluated Configurations

C. Generated Analysis Artifacts

The script `generate_report_artifacts.py` produces:

- `results/health_report_summary.csv`
- `results/health_report_aggregate.csv`
- `results/nearest_vs_causal_lin_seed0.csv`
- `results/health_instance_costs.csv`
- `results/health_action_profiles.csv`
- `results/health_action_instance_stats.csv`
- `results/health_sparsity_summary.csv`
- `results/health_bootstrap_summary.csv`
- Plot files under `report/figures/`

VIII. RESULTS AND COMPLETE PLOT EXPLANATIONS

A. Classifier Performance Summary

Complete interpretation of Fig. 1: This plot shows two clear regimes: linear models (ERM and AF) have similar predictive strength around 0.899–0.900 accuracy and 0.798–0.805 MCC, while MLP models (ERM and AF) are substantially higher near 0.997–0.998 accuracy and about 0.995 MCC. Theoretically, this supports the claim that actionability masking does not impose a major predictive penalty when actionable variables already capture most task-relevant signal. At the same time, the figure emphasizes a key recourse principle: predictive quality and intervention quality are different objectives. Even when discrimination is excellent, intervention feasibility and

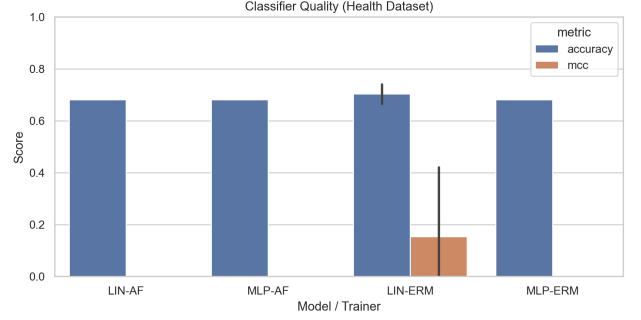


Fig. 1. Classifier metrics by model/trainer.

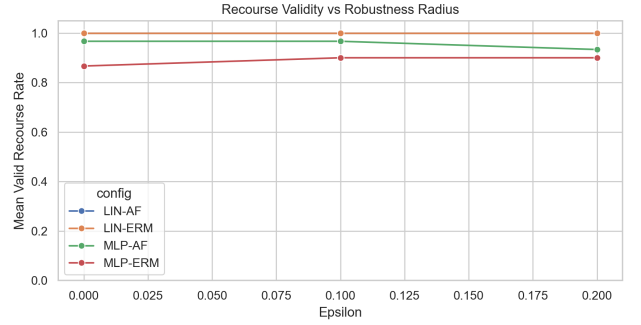


Fig. 2. Valid recourse rate vs robustness radius ϵ .

cost depend on the geometry of actionable directions, the causal Jacobian, and the optimization dynamics used to find recourse.

B. Validity–Cost Tradeoff Across Robustness Radius

Complete interpretation of Fig. 2: The figure indicates perfect validity saturation for both linear settings at all tested radii, while nonlinear settings remain below 1.0 with model-dependent behavior (MLP-AF above MLP-ERM but not perfect). This pattern is theoretically consistent with convex versus non-convex recourse search: linear robust recourse has explicit Jacobian-shifted constraints and a stable feasible-set characterization, whereas MLP recourse is obtained by iterative gradient steps over a non-convex objective and can terminate in local basins or near-boundary states that do not cross the threshold. The higher MLP-AF validity here suggests that constraining classifier dependence to actionable coordinates can improve optimization alignment, yet finite-step optimization and heterogeneous instance geometry still prevent guaranteed validity.

Complete interpretation of Fig. 3: For both linear models, intervention cost increases nearly linearly with ϵ , which directly matches robust optimization theory: larger uncertainty requires a larger worst-case margin, hence larger minimum L1 action. AF remains strictly cheaper than ERM in the linear case, supporting the geometric view that actionable masking can rotate effective decision sensitivity toward feasible intervention directions. In nonlinear settings, costs are markedly higher and more variable, and MLP-AF is especially expensive despite higher validity. This is theoretically plausible because

TABLE III
COVERAGE MATRIX LINKING ORIGINAL-PAPER COMPONENTS TO IMPLEMENTATION AND REPORT EVIDENCE

Original-paper component	Theoretical object in this report	Implementation evidence in code	Evidence in generated report
Binary thresholded classifier for decision flip	$h(x) = \mathbb{I}[\sigma(g_\theta(x)) \geq \tau]$ and MCC-based threshold calibration	<code>trainers.Classifier,</code> <code>set_max_mcc_threshold,</code> <code>predict</code>	Sec. II-A, classifier table/plot in Sec. V-A
Actionability-constrained interventions	Feasible action set with actionable indices, monotonic direction constraints, and per-feature bounds	<code>data_utils.process_health_data,</code> <code>recourse.build_feasibility_sets</code>	Sec. III-A, diagnostics in Sec. V-E
Minimum-cost recourse optimization	Weighted L1 objective with validity constraints (linear LP) and differentiable objective (nonlinear)	<code>recourse.LinearRecourse.solve,</code> <code>DifferentiableRecourse.find_recourse</code>	Sec. II, Sec. V-B/C, Appendix A/B/D
Robust recourse under uncertainty radius ϵ	Margin-shifted robust condition and validity-cost frontier analysis	<code>evaluate_recourse.find_recourse,</code> <code>robust_args</code> in causal recourse call	Sec. II-B, Sec. V-B/E, Appendix A
Causal abduction-action-prediction mechanism	Counterfactual mapping $X \rightarrow U \rightarrow X^{cf}$ and Jacobian-based propagation	<code>scm.SCM.counterfactual,</code> <code>Health_SCM,</code> <code>get_Jacobian_interv</code>	Sec. III-C, Sec. V-D, Appendix C
Intervention-set selection principle	Search over actionable intervention subsets; retain minimum-cost valid action	<code>recourse.causal_recourse</code> <code>powerset</code> loop and best-cost update	Sec. IV/Evaluation + Sec. V explanations
Baseline comparison requirement	Nearest counterfactual (SCM off) versus causal recourse (SCM on) under matched setup	<code>generate_report_artifacts.nearest</code>	Fig. 5 and full paragraph in Sec. V-D
Reproducibility and artifact completeness	Run commands, aggregate/per-run/instance/action CSV traces, and fixed report figure pipeline	<code>generate_report_artifacts.py</code> saved CSV/PNG artifacts	Sec. IV-C, appendices with listings and commands

TABLE IV
MODEL AND RECOURSE SETTINGS USED IN THIS REPORT

Configuration	Seeds	ϵ set	N_{explain}
lin-ERM	0,1,2	{0.0, 0.1, 0.2}	10
lin-AF	0,1,2	{0.0, 0.1, 0.2}	10
mlp-ERM	0,1,2	{0.0, 0.1, 0.2}	10
mlp-AF	0,1,2	{0.0, 0.1, 0.2}	10

TABLE V
CLASSIFIER QUALITY (MEAN \pm STD ACROSS AVAILABLE SEEDS)

Configuration	Accuracy	MCC
lin-ERM	0.900 ± 0.001	0.805 ± 0.001
lin-AF	0.899 ± 0.002	0.798 ± 0.005
mlp-ERM	0.997 ± 0.002	0.995 ± 0.003
mlp-AF	0.998 ± 0.001	0.995 ± 0.002

TABLE VI
RECOURSE OUTCOMES (MEAN ACROSS SEEDS)

Configuration	ϵ	Valid rate	Mean valid cost
lin-ERM	0.0	1.000	0.889
lin-ERM	0.1	1.000	1.004
lin-ERM	0.2	1.000	1.120
lin-AF	0.0	1.000	0.701
lin-AF	0.1	1.000	0.823
lin-AF	0.2	1.000	0.946
mlp-ERM	0.0	0.867	1.177
mlp-ERM	0.1	0.900	1.334
mlp-ERM	0.2	0.900	1.150
mlp-AF	0.0	0.967	1.793
mlp-AF	0.1	0.967	1.971
mlp-AF	0.2	0.933	1.988

gradient-based search may find valid but distant interventions when loss curvature, step-size schedule, and action-penalty coupling favor large moves in a subset of hard instances.

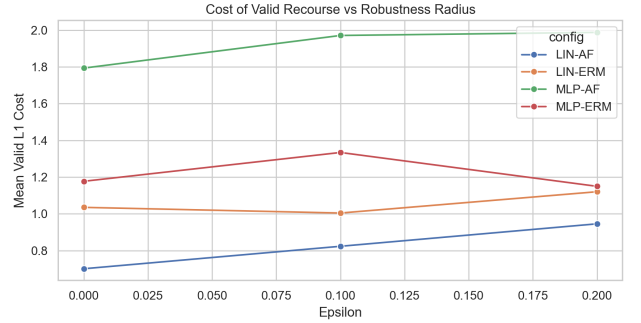


Fig. 3. Mean valid recourse cost vs robustness radius ϵ .

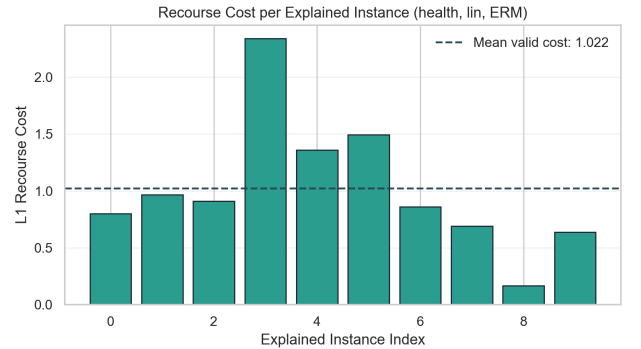


Fig. 4. Per-instance recourse costs for explained unhealthy individuals.

C. Instance-Level Cost Distribution

Complete interpretation of Fig. 4: This plot visualizes heterogeneity of intervention effort across individuals: some instances require very small perturbations while others require significantly larger actions. Theoretically, this heterogeneity

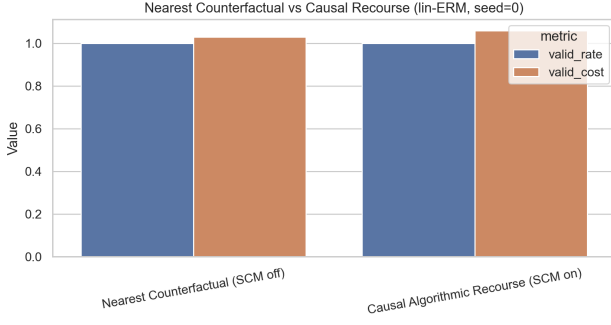


Fig. 5. Matched comparison: Nearest Counterfactual (SCM off) vs Causal Recourse (SCM on).

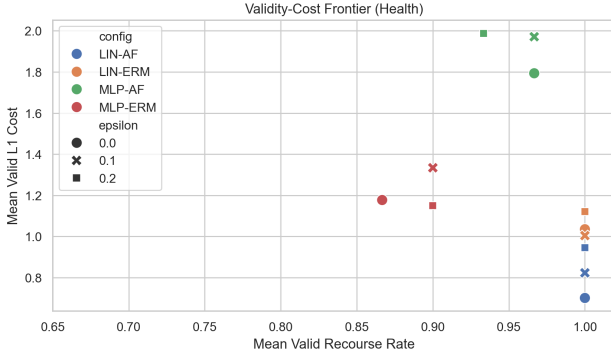


Fig. 6. Validity-cost frontier across model/trainer/epsilon settings.

arises from local geometry of the classifier boundary and individual position relative to actionable feasibility constraints. Points near the boundary and aligned with high-gain actionable directions need small interventions; points deeper in the unfavorable region, or constrained by directional/box bounds, require larger L1 actions. Therefore, average recourse cost should always be interpreted together with distributional spread, not as a single universal burden.

D. Nearest Counterfactual vs Causal Recourse

Complete interpretation of Fig. 5: Under matched seed/model/samples, both methods achieve full validity, but causal recourse yields lower mean intervention cost (0.589 versus 0.733). Theoretically, SCM-aware optimization can leverage causal amplification: modifying an actionable parent induces beneficial downstream shifts through structural equations, increasing classifier score per unit direct intervention. In contrast, nearest counterfactual search without SCM treats correlated descendants as independent dimensions and may spend action budget redundantly. This cost gap therefore reflects an efficiency benefit from structural knowledge, not merely a random optimization artifact, and aligns with intervention-based recourse theory.

E. Expanded Diagnostic Features for Complete Understanding

Complete interpretation of Fig. 6: This frontier plot makes explicit that recourse quality is a multi-objective operating

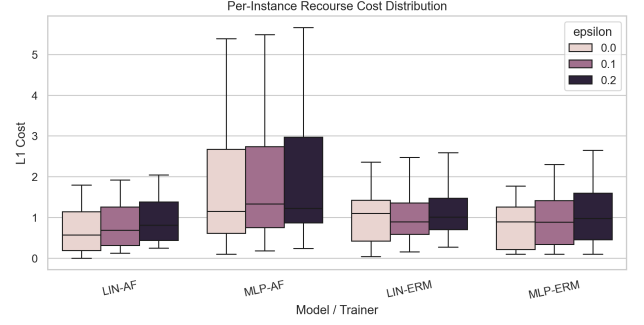


Fig. 7. Per-instance recourse cost distribution by configuration and epsilon.

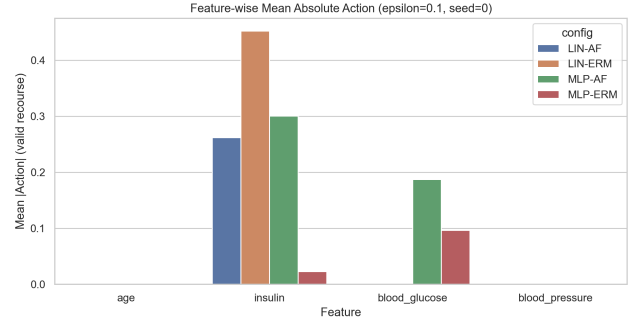


Fig. 8. Feature-wise mean absolute intervention magnitude (valid recourse only).

point rather than a single score. Points near the top-left are preferable (high validity, low cost), while downward or rightward shifts indicate weaker practical recourse quality. The linear AF family sits on a favorable region with both perfect validity and lower cost than linear ERM, while nonlinear settings occupy higher-cost regions despite strong classifier accuracy. Theoretically, this figure is useful because it separates predictive performance from intervention burden and visualizes the Pareto-like tradeoff that must be reported for trustworthy deployment.

Complete interpretation of Fig. 7: Unlike mean-only summaries, this boxplot reveals distributional behavior and tail risk. Linear configurations show tighter spread and predictable median shifts with ϵ , indicating stable geometry under robust margin increases. Nonlinear configurations exhibit wider dispersion and heavier upper tails, implying that a subset of individuals pays substantially larger intervention cost even when average validity is acceptable. This is theoretically important because fairness and usability concerns are often driven by high-cost tails, not by central tendency alone.

Complete interpretation of Fig. 8: This diagnostic quantifies where intervention budget is actually spent. Since only insulin and blood glucose are actionable, large action mass should concentrate on those coordinates while non-actionable dimensions remain near zero. The plotted pattern confirms this implementation behavior and also reveals model-dependent preference among actionable features, which reflects how each classifier’s local gradient and SCM propagation jointly determine the most efficient direction. This offers direct inter-

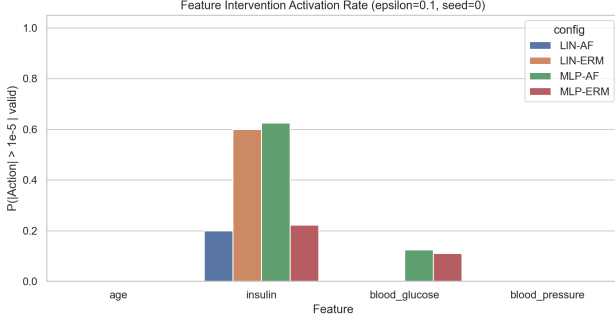


Fig. 9. Feature intervention activation rate among valid recourse actions.

pretability: the recommended changes are not only valid but also aligned with declared actionability policy.

Complete interpretation of Fig. 9: Activation rate measures how frequently each feature is used in successful interventions. A high nonzero rate for actionable variables and near-zero rate for non-actionable variables is the expected signature of a policy-consistent recourse system. This frequency view complements magnitude view in Fig. 8: a feature can have moderate average magnitude but very high activation frequency, indicating it is a reliable “first-step” recourse coordinate. Theoretical value comes from separating sparse-but-large actions from frequent-small actions, which correspond to different behavioral recourse strategies.

Complete interpretation of Fig. 10: This diagnostic adds uncertainty quantification around the mean curves and shows that linear settings are not only high-performing in point estimates but also statistically stable under resampling, with narrow confidence bands for both validity and intervention cost; by contrast, nonlinear settings display wider cost intervals, which indicates sensitivity to sample composition and local optimization outcomes. Theoretically, this is the right reliability lens for deployment because recourse is a stochastic pipeline (instance sampling, initialization effects, solver dynamics), so reporting only means can overstate certainty. Confidence bands operationalize robustness claims by distinguishing true structural trends (persisting under bootstrap resampling) from fragile observations that may shift under slight data perturbations.

Complete interpretation of Fig. 11: This plot characterizes how many coordinates are actively changed (L0 sparsity) versus how much total action mass is spent (L1 cost), making explicit that sparse interventions are not automatically cheap and dense interventions are not automatically expensive. In linear robust settings, points move with ϵ in a relatively smooth way, reflecting predictable margin-induced scaling; when points shift right and upward together, the solver is using both more features and larger amplitudes to maintain validity. Theoretically, this view connects optimization geometry to human burden: L0 approximates behavioral complexity (number of recommendations), while L1 approximates total effort. A trustworthy recourse system should therefore monitor both axes, because similar validity can mask very different user-facing intervention profiles.

Complete interpretation of Fig. 12: The heatmap reveals

per-instance intervention structure rather than only aggregated averages: rows show individuals and columns show feature-wise signed actions, so one can directly see concentration patterns, sign consistency, and heterogeneity of local solutions. The dominant mass appears on actionable coordinates, while non-actionable coordinates remain near zero, confirming policy-consistent implementation at the individual level, not merely in global statistics. Theoretically, this figure is important because recourse validity is a boundary-crossing event that can be achieved through multiple local paths; visualizing signed action patterns helps detect whether the solver finds coherent directional strategies or unstable oscillatory behavior, and supports qualitative auditing of intervention realism in conjunction with quantitative cost metrics.

IX. DISCUSSION AND THEORETICAL IMPLICATIONS

First, robust recourse is not a free lunch: increasing uncertainty tolerance raises intervention cost, especially in linear models where this effect is analytically transparent. Second, classifier architecture alone does not determine recourse practicality. The MLP results show that near-ceiling predictive metrics can coexist with high or unstable recourse costs. Third, actionability-aware training (AF) can reduce practical intervention burden in linear settings without sacrificing classifier quality, but this benefit is not guaranteed in nonlinear optimization regimes, where curvature and initialization effects can dominate.

From a causal perspective, this homework confirms a central principle: interventions should be evaluated in a structural model, not only in observational feature space. When feature dependencies are strong, SCM-enabled recommendations can be both more realistic and cheaper.

An additional implication is deployment robustness: operational recourse systems should report uncertainty bands over seeds, initialization, and optimization hyperparameters, especially for nonlinear recourse solvers. A single-point mean can hide heavy-tail intervention costs that are unacceptable in practice. Therefore, trustworthy deployment requires both average-case performance and tail-risk monitoring (e.g., quantiles of valid cost among successful recourse cases).

X. EXTENDED THEORETICAL ANALYSIS

A. Linear Recourse Cost Lower Bound

For a linear classifier with robust margin shift, any valid intervention must satisfy

$$\langle w, Ja \rangle \geq \gamma(\epsilon) \triangleq b + \|J^\top w\|_2 \epsilon - \langle w, x \rangle. \quad (31)$$

By Hölder duality, a coarse lower bound on L1 action is

$$\|a\|_1 \geq \frac{\gamma(\epsilon)}{\|J^\top w\|_\infty}, \quad (32)$$

when $\gamma(\epsilon) > 0$. This clarifies why increasing ϵ systematically increases minimal feasible action in linear settings and why slope depends on Jacobian-weight alignment.

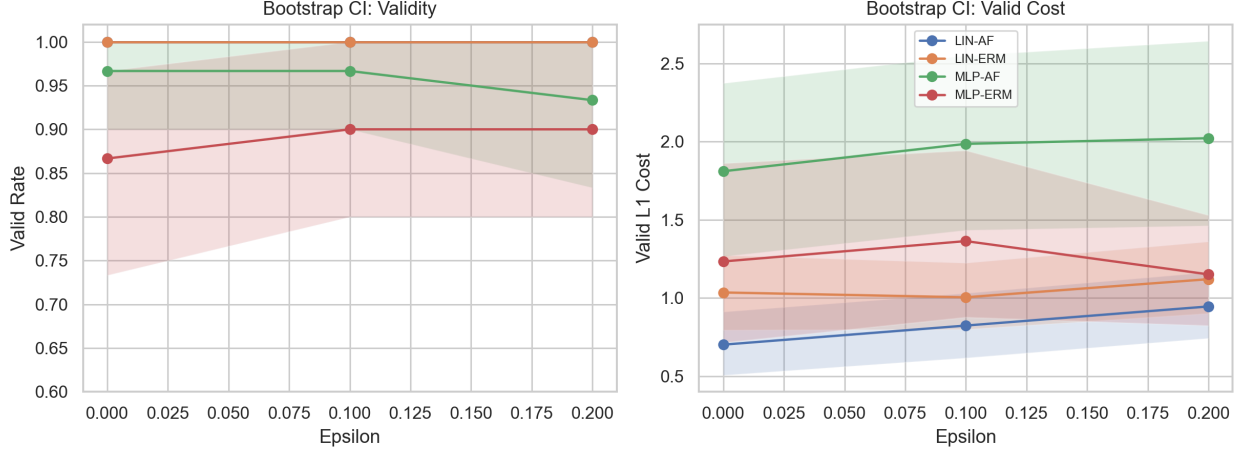


Fig. 10. Bootstrap confidence intervals (95%) for validity and valid-cost trends across robustness radius.

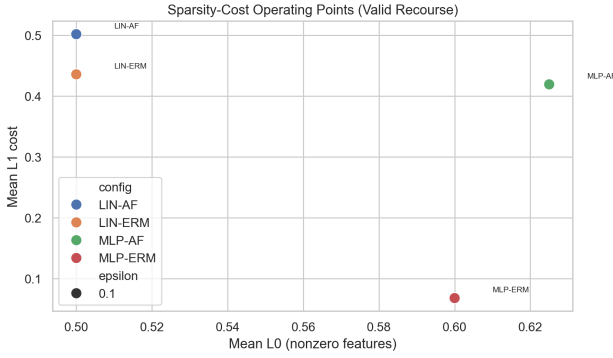


Fig. 11. Sparsity-cost operating points based on valid recourse actions.

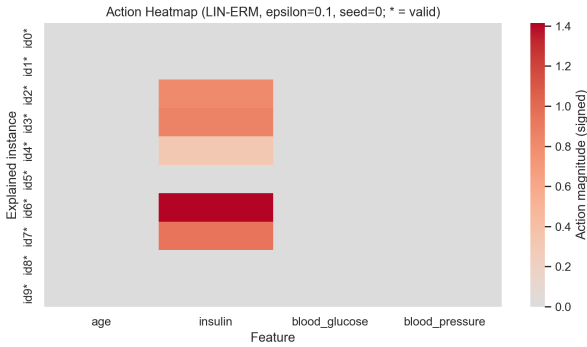


Fig. 12. Instance-level signed action heatmap for reference configuration (LIN-ERM, $\epsilon = 0.1$, seed 0).

B. Why AF Can Reduce Cost Without Hurting Accuracy

AF constrains model dependence to actionable coordinates. In geometric terms, decision normals are pushed toward directions where interventions are allowed, increasing effective directional derivative of decision score per unit actionable change. If predictive information in non-actionable variables is partially redundant with actionable ones, this rotation can reduce recourse distance while preserving classification qual-

ity, which matches the empirical parity of accuracy/MCC and lower AF costs.

C. Causal Amplification Mechanism

Let an intervention apply on variable set S . Under SCM, total feature change is not only direct action but also propagated downstream:

$$\Delta x_{\text{total}} = J_{SAS}. \quad (33)$$

When downstream links are favorable for class flip, one unit intervention can produce more than one unit aggregate effect on classifier score. Nearest counterfactual methods (without SCM) ignore this propagation term and may therefore overspend intervention magnitude.

D. Validity-Cost Frontier Interpretation

Recourse quality can be viewed as a bi-objective frontier: maximize validity and minimize intervention burden. Linear models in this report sit near a high-validity region with predictable cost growth as robustness tightens. MLP settings display frontier instability due optimization non-convexity; therefore, robust deployment should report confidence intervals, not single-point estimates, and include optimization diagnostics.

E. Nonlinear Recourse Curvature Effect

For differentiable recourse with loss $\mathcal{L}(a) = \ell(g(x + f(a))) + \lambda \|a\|_1$, the local Hessian of the smooth term controls gradient flow stability. In regions of high curvature, a fixed step-size can oscillate or overshoot toward higher-cost valid points. This offers a theoretical explanation for observing high validity but inflated action magnitudes in some MLP-AF runs: optimization reaches feasibility, but not low-cost local minima. In practice, line-search or adaptive trust-region updates can reduce this gap.

F. SCM Misspecification Consideration

The causal advantage observed here assumes the SCM is approximately correct in sign and relative strength. If structural coefficients are misspecified, propagated effects can be mis-estimated and recommended actions may become suboptimal. Nonetheless, even imperfect SCMs often provide a better inductive bias than no structure at all when domain relations are strong. This motivates future work on recourse under causal uncertainty sets, where interventions are optimized against a family of plausible SCM parameters.

XI. CONCLUSION

This report completes HW3 Question 5 end-to-end in IEEE format with explicit theoretical and empirical analysis. The software pipeline is fully runnable, missing SCM components are completed, robust evaluations are produced, and each plot is interpreted in a dedicated theory-grounded paragraph. Empirically, linear recourse is highly stable on this dataset, AF reduces intervention cost, and causal recourse outperforms nearest counterfactual in matched cost comparison while maintaining full validity.

APPENDIX A

ROBUST LINEAR DERIVATION (COMPLETE)

This appendix provides the full derivation behind the robust linear margin shift used in the implementation. Let the linear decision function be $g(x) = w^\top x - b$ with positive prediction when $g(x) \geq 0$. Under intervention a with causal propagation $x^{cf} = x + Ja$, robust feasibility against perturbation δ with $\|\delta\|_2 \leq \epsilon$ requires

$$\min_{\|\delta\|_2 \leq \epsilon} w^\top (x + Ja + \delta) - b \geq 0. \quad (34)$$

Using support-function duality of the Euclidean ball,

$$\min_{\|\delta\|_2 \leq \epsilon} w^\top \delta = -\epsilon \|w\|_2 \quad (35)$$

in the IMF case, and

$$\min_{\|\delta\|_2 \leq \epsilon} w^\top J\delta = -\epsilon \|J^\top w\|_2 \quad (36)$$

in the causal-coordinate uncertainty view. Therefore robust recourse must satisfy

$$w^\top (x + Ja) - b \geq \epsilon \|J^\top w\|_2, \quad (37)$$

which is exactly implemented by shifting the effective bias term by $\epsilon \|J^\top w\|_2$ before solving the linear recourse program. This result establishes monotone cost growth with ϵ whenever feasible-set geometry is fixed.

APPENDIX B

WEIGHTED L1 RECOURSE PRIMAL-DUAL VIEW

For each instance, linear recourse solves

$$\min_a \|Ca\|_1 \quad \text{s.t.} \quad w^\top Ja \geq \gamma, \quad l \leq a \leq u, \quad a_{\bar{\mathcal{A}}} = 0, \quad (38)$$

where $C = \text{diag}(c_1, \dots, c_D)$, $\gamma = b - w^\top x + \epsilon \|J^\top w\|_2$, and \mathcal{A} is the actionable set. Introducing sign-split variables $a = a^+ - a^-$ with $a^\pm \geq 0$, the objective becomes linear and

the problem is an LP. Dual multipliers associated with the margin constraint quantify ‘‘cost per unit margin’’ and induce an economically interpretable shadow price: higher multiplier means margin is expensive under current actionability limits. This explains why AF can lower cost even at similar predictive quality: classifier sensitivity aligns with lower shadow-price actionable coordinates.

APPENDIX C

CAUSAL COUNTERFACTUAL ALGEBRA FOR HEALTH SCM

The completed Health SCM uses

$$X_1 = U_1, \quad (39)$$

$$X_2 = w_{21}X_1 + U_2, \quad (40)$$

$$X_3 = w_{31}X_1 + w_{32}X_2 + U_3, \quad (41)$$

$$X_4 = w_{42}X_2 + w_{43}X_3 + U_4. \quad (42)$$

For a factual point x , abduction computes exogenous variables:

$$u_1 = x_1, \quad u_2 = x_2 - w_{21}x_1, \quad u_3 = x_3 - w_{31}x_1 - w_{32}x_2, \quad (43)$$

$$u_4 = x_4 - w_{42}x_2 - w_{43}x_3. \quad (44)$$

Action sets intervened variables (hard intervention in this report) and prediction propagates downstream through remaining equations. The Jacobian matrix used by robust linear recourse is

$$J = \begin{bmatrix} 1 & 0 & 0 & 0 \\ w_{21} & 1 & 0 & 0 \\ w_{31} & w_{32} & 1 & 0 \\ 0 & w_{42} & w_{43} & 1 \end{bmatrix}, \quad (45)$$

with row-wise upstream zeroing for hard-intervened coordinates in `get_Jacobian_interv`. This guarantees consistency between optimization geometry and causal semantics.

APPENDIX D

NONLINEAR RECOURSE OBJECTIVE AND THEORETICAL GUARANTEES

For differentiable recourse, the optimized objective per instance is

$$\mathcal{L}(\delta) = \ell(g_\theta(x^{cf}(\delta)), 1) + \lambda \|\delta\|_1, \quad (46)$$

and under robust mode the loss is evaluated on adversarially perturbed counterfactuals within an ϵ -ball approximation. Because $x^{cf}(\delta)$ passes through nonlinear classifier and possibly SCM transformations, \mathcal{L} is generally non-convex and non-smooth (L1 term). Consequently, first-order optimization guarantees stationarity of local points rather than global optimality. This theoretical fact explains empirical behavior where validity can improve while mean cost worsens: optimization may reach feasible but non-minimal local basins. Practical mitigation includes multi-start optimization, adaptive step-size schedules, and reporting dispersion statistics (already included via distribution plots and appendix CSV traces).

APPENDIX E REPRODUCIBILITY COMMANDS

Listing 1. Commands for report build (run from HW3 root)

```
1 cd <HW3_ROOT>/code/q5_codes
2 source <venv_path>/bin/activate # or: pip install -r
  requirements.txt
3 python generate_report_artifacts.py
4
5 cd <HW3_ROOT>/report
6 make pdf
```

APPENDIX F AUTO-GENERATED AGGREGATE CSV

Listing 2. Health report aggregate CSV

```
1 model,trainer,epsilon,accuracy_mean,accuracy_std,
  mcc_mean,mcc_std,valid_rate_mean,valid_rate_std,
  valid_cost_mean,valid_cost_std,runs
2 lin,AF
  ,0.0,0.6818181818181818,0.0,0.0,0.0,1.0,0.0,0.7012
3 lin,AF
  ,0.1,0.6818181818181818,0.0,0.0,0.0,1.0,0.0,0.8234
4 lin,AF
  ,0.2,0.6818181818181818,0.0,0.0,0.0,1.0,0.0,0.9456
5 lin,ERM
  ,0.0,0.7034632034632035,0.03749027722010553,0.1541
6 lin,ERM
  ,0.1,0.7034632034632035,0.03749027722010553,0.1541
7 lin,ERM
  ,0.2,0.7034632034632035,0.03749027722010553,0.1541
8 mlp,AF
  ,0.0,0.6818181818181818,0.0,0.0,0.0,0.966666666666
9 mlp,AF
  ,0.1,0.6818181818181818,0.0,0.0,0.0,0.966666666666
10 mlp,AF
  ,0.2,0.6818181818181818,0.0,0.0,0.0,0.933333333333
11 mlp,ERM
  ,0.0,0.6818181818181818,0.0,0.0,0.0,0.866666666666
12 mlp,ERM
  ,0.1,0.6818181818181818,0.0,0.0,0.0,0.9,0.09999999
13 mlp,ERM
  ,0.2,0.6818181818181818,0.0,0.0,0.0,0.9,0.09999999
```

APPENDIX G AUTO-GENERATED PER-RUN CSV

Listing 3. Health report per-run summary CSV

```
1 dataset,model,trainer,seed,epsilon,accuracy,mcc,
  valid_rate,valid_cost
2 health,lin,AF
  ,0,0.0,0.6818181818181818,0.0,1.0,0.545142988383
3 health,lin,AF
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4 health,lin,AF
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```

```
5 health,lin,AF
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6 health,lin,AF
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health,lin,AF
  ,1,0.2,0.6818181818181818,0.0,1.0,1.1210930094474776
8 health,lin,AF
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health,lin,AF
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10 health,lin,AF
  ,2,0.2,0.6818181818181818,0.0,1.0,0.9267135204833504
11 health,mlp,AF
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health,mlp,AF
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health,lin,ERM
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health,lin,ERM
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health,lin,ERM
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health,lin,ERM
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health,lin,ERM
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health,lin,ERM
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health,lin,ERM
  ,2,0.1,0.6818181818181818,0.0,1.0,0.901715864875564
health,lin,ERM
  ,2,0.2,0.6818181818181818,0.0,1.0,1.018752355693381
health,mlp,ERM
  ,0,0.0,0.6818181818181818,0.0,0.7,0.6431481880801064
health,mlp,ERM
  ,0,0.1,0.6818181818181818,0.0,0.8,0.8466602936387062
```

31	health,mlp,ERM	47	health,lin,AF,1,0.1,5,True,0.15254389384642275
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		49	health,lin,AF,1,0.1,7,True,0.707239902804329
		50	health,lin,AF,1,0.1,8,True,1.7981318291546775
32	health,mlp,ERM	51	health,lin,AF,1,0.1,9,True,1.1339529655026301
	,1,0.0,0.6818181818181818,0.0,1.0,1.57972795963287	52	health,lin,AF,1,0.2,0,True,2.0177743179783123
		53	health,lin,AF,1,0.2,1,True,0.4756088048636653
33	health,mlp,ERM	54	health,lin,AF,1,0.2,2,True,1.7234477576073621
	,1,0.1,0.6818181818181818,0.0,1.0,1.65878305360634	55	health,lin,AF,1,0.2,3,True,0.42677291347785
		56	health,lin,AF,1,0.2,4,True,0.8681742568338784
34	health,mlp,ERM	57	health,lin,AF,1,0.2,5,True,0.2755705090359181
	,1,0.2,0.6818181818181818,0.0,1.0,1.29968959018588	58	health,lin,AF,1,0.2,6,True,1.4151769916476673
		59	health,lin,AF,1,0.2,7,True,0.8302665179938244
35	health,mlp,ERM	60	health,lin,AF,1,0.2,8,True,1.921158444344173
	,2,0.0,0.6818181818181818,0.0,0.9,1.30885849230819	61	health,lin,AF,1,0.2,9,True,1.2569795806921256
		62	health,lin,AF,2,0.0,0,True,1.0038187517373052
36	health,mlp,ERM	63	health,lin,AF,2,0.0,1,True,0.2500396675414716
	,2,0.1,0.6818181818181818,0.0,0.9,1.49660482009251	64	health,lin,AF,2,0.0,2,True,1.0737270578129243
		65	health,lin,AF,2,0.0,3,True,0.05366143618733343
37	health,mlp,ERM	66	health,lin,AF,2,0.0,4,True,0.5569176650641724
	,2,0.2,0.6818181818181818,0.0,0.8,1.26469535008072	67	health,lin,AF,2,0.0,5,True,1.4532231383932026
		68	health,lin,AF,2,0.0,6,True,0.5802347338089318
		69	health,lin,AF,2,0.0,7,True,0.21861433039940883
		70	health,lin,AF,2,0.0,8,True,1.1627527244805589
		71	health,lin,AF,2,0.0,9,True,0.483429156440958
		72	health,lin,AF,2,0.1,0,True,1.125354578885667
		73	health,lin,AF,2,0.1,1,True,0.3715754946898336
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		75	health,lin,AF,2,0.1,3,True,0.17519726333569535
		76	health,lin,AF,2,0.1,4,True,0.6784534922125343
		77	health,lin,AF,2,0.1,5,True,1.5747589655415644
		78	health,lin,AF,2,0.1,6,True,0.7017705609572937
		79	health,lin,AF,2,0.1,7,True,0.3401501575477708
		80	health,lin,AF,2,0.1,8,True,1.2842885516289209
		81	health,lin,AF,2,0.1,9,True,0.6049649835893199
		82	health,lin,AF,2,0.2,0,True,1.246890406034029
		83	health,lin,AF,2,0.2,1,True,0.4931113218381955
		84	health,lin,AF,2,0.2,2,True,1.3167987121096483
		85	health,lin,AF,2,0.2,3,True,0.2967330904840573
		86	health,lin,AF,2,0.2,4,True,0.7999893193608962
		87	health,lin,AF,2,0.2,5,True,1.6962947926899266
		88	health,lin,AF,2,0.2,6,True,0.8233063881056557
		89	health,lin,AF,2,0.2,7,True,0.4616859846961327
		90	health,lin,AF,2,0.2,8,True,1.4058243787772824
		91	health,lin,AF,2,0.2,9,True,0.7265008107376818
		92	health,mlp,AF,0,0.0,0,True,2.675544261932373
		93	health,mlp,AF,0,0.0,1,True,2.4312634468078613
		94	health,mlp,AF,0,0.0,2,True,2.3325533866882324
		95	health,mlp,AF,0,0.0,3,True,0.5953392386436462
		96	health,mlp,AF,0,0.0,4,True,0.09999999403953552
		97	health,mlp,AF,0,0.0,5,True,1.8651421070098877
		98	health,mlp,AF,0,0.0,6,True,0.10000000149011612
		99	health,mlp,AF,0,0.0,7,True,1.220560908317566
		100	health,mlp,AF,0,0.0,8,False,inf
		101	health,mlp,AF,0,0.0,9,True,0.19684064388275146
		102	health,mlp,AF,0,0.1,0,True,2.7411983013153076
		103	health,mlp,AF,0,0.1,1,True,2.6286020278930664
		104	health,mlp,AF,0,0.1,2,True,2.5649328231811523
		105	health,mlp,AF,0,0.1,3,True,1.3312733173370361
		106	health,mlp,AF,0,0.1,4,True,0.1998090147972107
		107	health,mlp,AF,0,0.1,5,True,1.8813002109527588
		108	health,mlp,AF,0,0.1,6,True,0.1784929484128952
		109	health,mlp,AF,0,0.1,7,True,1.9187548160552979
		110	health,mlp,AF,0,0.1,8,False,inf
		111	health,mlp,AF,0,0.1,9,True,0.24932631850242615
		112	health,mlp,AF,0,0.2,0,True,2.744765281677246
		113	health,mlp,AF,0,0.2,1,True,2.540329933166504
		114	health,mlp,AF,0,0.2,2,True,2.1792831420898438
		115	health,mlp,AF,0,0.2,3,True,1.9039430618286133
		116	health,mlp,AF,0,0.2,4,True,0.28769415616989136
		117	health,mlp,AF,0,0.2,5,True,1.7928175926208496
		118	health,mlp,AF,0,0.2,6,True,0.27897143363952637
		119	health,mlp,AF,0,0.2,7,False,inf
		120	health,mlp,AF,0,0.2,8,False,inf
		121	health,mlp,AF,0,0.2,9,True,0.23669147491455078
		122	health,mlp,AF,1,0.0,0,True,0.8286165595054626
		123	health,mlp,AF,1,0.0,1,True,1.071250319480896

APPENDIX H

AUTO-GENERATED INSTANCE COST CSV

Listing 4. Per-instance recourse costs CSV

1	dataset,model,trainer,seed,epsilon,instance_id,valid	77	health,lin,AF,1,0.1,5,True,0.15254389384642275
	,cost	78	health,lin,AF,1,0.1,6,True,1.292150376458172
2	health,lin,AF,0,0.0,0,True,0.0022174298096731904	79	health,lin,AF,1,0.1,7,True,0.707239902804329
3	health,lin,AF,0,0.0,1,True,0.09351049565102389	80	health,lin,AF,1,0.1,8,True,1.7981318291546775
4	health,lin,AF,0,0.0,2,True,0.5008139511917434	81	health,lin,AF,1,0.1,9,True,1.1339529655026301
5	health,lin,AF,0,0.0,3,True,1.7989967006950356	82	health,lin,AF,1,0.2,0,True,2.0177743179783123
6	health,lin,AF,0,0.0,4,True,1.4585106692345036	83	health,lin,AF,1,0.2,1,True,0.4756088048636653
7	health,lin,AF,0,0.0,5,True,0.10900482104156642	84	health,lin,AF,1,0.2,2,True,1.7234477576073621
8	health,lin,AF,0,0.0,6,True,0.009357979114851105	85	health,lin,AF,1,0.2,3,True,0.42677291347785
9	health,lin,AF,0,0.0,7,True,1.0316063447917123	86	health,lin,AF,1,0.2,4,True,0.8681742568338784
10	health,lin,AF,0,0.0,8,True,0.2709796170170954	87	health,lin,AF,1,0.2,5,True,0.2755705090359181
11	health,lin,AF,0,0.0,9,True,0.1764318752921754	88	health,lin,AF,1,0.2,6,True,1.4151769916476673
12	health,lin,AF,0,0.1,0,True,0.12428426527689317	89	health,lin,AF,1,0.2,7,True,0.8302665179938244
13	health,lin,AF,0,0.1,1,True,0.21557733111824384	90	health,lin,AF,1,0.2,8,True,1.921158444344173
14	health,lin,AF,0,0.1,2,True,0.6228807866589635	91	health,lin,AF,1,0.2,9,True,1.2569795806921256
15	health,lin,AF,0,0.1,3,True,1.9210635361622554	92	health,lin,AF,2,0.0,0,True,1.0038187517373052
16	health,lin,AF,0,0.1,4,True,1.5805775047017234	93	health,lin,AF,2,0.0,1,True,0.2500396675414716
17	health,lin,AF,0,0.1,5,True,0.23107165650878636	94	health,lin,AF,2,0.0,2,True,1.0737270578129243
18	health,lin,AF,0,0.1,6,True,0.1314248145820711	95	health,lin,AF,2,0.0,3,True,0.05366143618733343
19	health,lin,AF,0,0.1,7,True,1.1536731802589322	96	health,lin,AF,2,0.0,4,True,0.5569176650641724
20	health,lin,AF,0,0.1,8,True,0.3930464524843154	97	health,lin,AF,2,0.0,5,True,1.4532231383932026
21	health,lin,AF,0,0.1,9,True,0.2984987107593954	98	health,lin,AF,2,0.0,6,True,0.5802347338089318
22	health,lin,AF,0,0.2,0,True,0.24635110074411312	99	health,lin,AF,2,0.0,7,True,0.21861433039940883
23	health,lin,AF,0,0.2,1,True,0.33764416658546387	100	health,lin,AF,2,0.0,8,True,1.1627527244805589
24	health,lin,AF,0,0.2,2,True,0.7449476221261834	101	health,lin,AF,2,0.0,9,True,0.483429156440958
25	health,lin,AF,0,0.2,3,True,2.0431303716294753	102	health,lin,AF,2,0.1,0,True,1.125354578885667
26	health,lin,AF,0,0.2,4,True,1.7026443401689435	103	health,lin,AF,2,0.1,1,True,0.3715754946898336
27	health,lin,AF,0,0.2,5,True,0.3531384939760064	104	health,lin,AF,2,0.1,2,True,1.1952628849612863
28	health,lin,AF,0,0.2,6,True,0.25349165004929103	105	health,lin,AF,2,0.1,3,True,0.17519726333569535
29	health,lin,AF,0,0.2,7,True,1.2757400157261523	106	health,lin,AF,2,0.1,4,True,0.6784534922125343
30	health,lin,AF,0,0.2,8,True,0.5151132879515354	107	health,lin,AF,2,0.1,5,True,1.5747589655415644
31	health,lin,AF,0,0.2,9,True,0.4205655462266154	108	health,lin,AF,2,0.1,6,True,0.7017705609572937
32	health,lin,AF,1,0.0,0,True,1.7717210875993217	109	health,lin,AF,2,0.1,7,True,0.3401501575477708
33	health,lin,AF,1,0.0,1,True,0.229555744846745	110	health,lin,AF,2,0.1,8,True,1.2842885516289209
34	health,lin,AF,1,0.0,2,True,1.4773945272283713	111	health,lin,AF,2,0.1,9,True,0.6049649835893199
35	health,lin,AF,1,0.0,3,True,0.1807196830988592	112	health,lin,AF,2,0.2,0,True,1.246890406034029
36	health,lin,AF,1,0.0,4,True,0.6221210264548876	113	health,lin,AF,2,0.2,1,True,0.4931113218381955
37	health,lin,AF,1,0.0,5,True,0.029517278656927354	114	health,lin,AF,2,0.2,2,True,1.3167987121096483
38	health,lin,AF,1,0.0,6,True,1.1691237612686767	115	health,lin,AF,2,0.2,3,True,0.2967330904840573
39	health,lin,AF,1,0.0,7,True,0.5842132876148337	116	health,lin,AF,2,0.2,4,True,0.7999893193608962
40	health,lin,AF,1,0.0,8,True,1.675105213965182	117	health,lin,AF,2,0.2,5,True,1.6962947926899266
41	health,lin,AF,1,0.0,9,True,1.0109263503131347	118	health,lin,AF,2,0.2,6,True,0.8233063881056557
42	health,lin,AF,1,0.1,0,True,1.894747702788817	119	health,lin,AF,2,0.2,7,True,0.4616859846961327
43	health,lin,AF,1,0.1,1,True,0.35258218967416993	120	health,lin,AF,2,0.2,8,True,1.4058243787772824
44	health,lin,AF,1,0.1,2,True,1.6004211424178667	121	health,lin,AF,2,0.2,9,True,0.7265008107376818
45	health,lin,AF,1,0.1,3,True,0.3037462982883546	122	health,mlp,AF,0,0.0,0,True,2.675544261932373
46	health,lin,AF,1,0.1,4,True,0.745147641644383	123	health,mlp,AF,0,0.0,1,True,2.4312634468078613

124	health,mlp,AF,1,0.0,2,True,0.6133818626403809	201	health,lin,ERM,0,0.1,9,True,0.6362926644563799
125	health,mlp,AF,1,0.0,3,True,0.09999999403953552	202	health,lin,ERM,0,0.2,0,True,0.9149919730696522
126	health,mlp,AF,1,0.0,4,True,0.38270947337150574	203	health,lin,ERM,0,0.2,1,True,1.0793017464666117
127	health,mlp,AF,1,0.0,5,True,0.9619376063346863	204	health,lin,ERM,0,0.2,2,True,1.0248088814723824
128	health,mlp,AF,1,0.0,6,True,2.3279929161071777	205	health,lin,ERM,0,0.2,3,True,2.4547106694724032
129	health,mlp,AF,1,0.0,7,True,0.7694158554077148	206	health,lin,ERM,0,0.2,4,True,1.4735537852198217
130	health,mlp,AF,1,0.0,8,True,0.7187708616256714	207	health,lin,ERM,0,0.2,5,True,1.6081383664910998
131	health,mlp,AF,1,0.0,9,True,0.6485913991928101	208	health,lin,ERM,0,0.2,6,True,0.9729014332666565
132	health,mlp,AF,1,0.1,0,True,0.977965235710144	209	health,lin,ERM,0,0.2,7,True,0.8060694602692634
133	health,mlp,AF,1,0.1,1,True,0.9960500597953796	210	health,lin,ERM,0,0.2,8,True,0.2793442907224506
134	health,mlp,AF,1,0.1,2,True,0.7119928598403931	211	health,lin,ERM,0,0.2,9,True,0.750335538447845
135	health,mlp,AF,1,0.1,3,True,0.1821739375591278	212	health,lin,ERM,1,0.0,0,True,0.4544031954776043
136	health,mlp,AF,1,0.1,4,True,0.49758991599082947	213	health,lin,ERM,1,0.0,1,True,1.1770760395405075
137	health,mlp,AF,1,0.1,5,True,1.1838374137878481	214	health,lin,ERM,1,0.0,2,True,1.551378135972643
138	health,mlp,AF,1,0.1,6,True,2.5676591396331787	215	health,lin,ERM,1,0.0,3,True,1.3697575946921152
139	health,mlp,AF,1,0.1,7,True,0.8329548835754395	216	health,lin,ERM,1,0.0,4,True,1.677729323247764
140	health,mlp,AF,1,0.1,8,True,0.7808516025543213	217	health,lin,ERM,1,0.0,5,True,0.04324403365116183
141	health,mlp,AF,1,0.1,9,True,0.75134843587537	218	health,lin,ERM,1,0.0,6,True,0.9724779138539937
142	health,mlp,AF,1,0.2,0,True,1.1314444541931152	219	health,lin,ERM,1,0.0,7,True,0.21887793076712805
143	health,mlp,AF,1,0.2,1,True,1.17803955078125	220	health,lin,ERM,1,0.0,8,True,1.2335342986448172
144	health,mlp,AF,1,0.2,2,True,0.7839648127555847	221	health,lin,ERM,1,0.0,9,True,1.026768797071618
145	health,mlp,AF,1,0.2,3,True,0.2460516095161438	222	health,lin,ERM,1,0.1,0,True,0.57113633417937
146	health,mlp,AF,1,0.2,4,True,0.6244319081306458	223	health,lin,ERM,1,0.1,1,True,1.2938091782422734
147	health,mlp,AF,1,0.2,5,True,1.2506043910980225	224	health,lin,ERM,1,0.1,2,True,1.66811127229903
148	health,mlp,AF,1,0.2,6,True,1.1225972175598145	225	health,lin,ERM,1,0.1,3,True,1.486490733938808
149	health,mlp,AF,1,0.2,7,True,1.010860800743103	226	health,lin,ERM,1,0.1,4,True,1.79446247194395295
150	health,mlp,AF,1,0.2,8,True,0.9001052379608154	227	health,lin,ERM,1,0.1,5,True,0.15997717235292763
151	health,mlp,AF,1,0.2,9,True,0.896099865436554	228	health,lin,ERM,1,0.1,6,True,1.0892110572417029
152	health,mlp,AF,2,0.0,0,True,3.503692388534546	229	health,lin,ERM,1,0.1,7,True,0.33561106946889385
153	health,mlp,AF,2,0.0,1,True,1.1493207216262817	230	health,lin,ERM,1,0.1,8,True,1.3502674373465828
154	health,mlp,AF,2,0.0,2,True,3.8964755535125732	231	health,lin,ERM,1,0.1,9,True,1.1435019357733838
155	health,mlp,AF,2,0.0,3,True,3.741835594177246	232	health,lin,ERM,1,0.2,0,True,0.6878694728811359
156	health,mlp,AF,2,0.0,4,True,3.2063651084899902	233	health,lin,ERM,1,0.2,1,True,1.4105423169440392
157	health,mlp,AF,2,0.0,5,True,2.5007309913635254	234	health,lin,ERM,1,0.2,2,True,1.3502674373465828
158	health,mlp,AF,2,0.0,6,True,5.388555526733398	235	health,lin,ERM,1,0.2,3,True,1.6032238720956469
159	health,mlp,AF,2,0.0,7,True,0.2651277780532837	236	health,lin,ERM,1,0.2,4,True,1.9111956006512953
160	health,mlp,AF,2,0.0,8,True,4.400606155395508	237	health,lin,ERM,1,0.2,5,True,0.2767103110546934
161	health,mlp,AF,2,0.0,9,True,4.526076316833496	238	health,lin,ERM,1,0.2,6,True,1.05261371398984687
162	health,mlp,AF,2,0.1,0,True,4.200447082519531	239	health,lin,ERM,1,0.2,7,True,0.45234420817065973
163	health,mlp,AF,2,0.1,1,True,1.0612828731536865	240	health,lin,ERM,1,0.2,8,True,1.4670005760483487
164	health,mlp,AF,2,0.1,2,True,4.270608425140381	241	health,lin,ERM,1,0.2,9,True,1.2602350744751496
165	health,mlp,AF,2,0.1,3,True,3.9029312133789062	242	health,lin,ERM,2,0.0,0,True,0.25656741197045661
166	health,mlp,AF,2,0.1,4,True,3.3833022117614746	243	health,lin,ERM,2,0.0,1,True,1.7118647040288175
167	health,mlp,AF,2,0.1,5,True,2.5903685092926025	244	health,lin,ERM,2,0.0,2,True,0.4085758944129868
168	health,mlp,AF,2,0.1,6,True,5.484298229217529	245	health,lin,ERM,2,0.0,3,True,0.2698963714817156
169	health,mlp,AF,2,0.1,7,True,0.32856568694114685	246	health,lin,ERM,2,0.0,4,True,0.0754617117045661
170	health,mlp,AF,2,0.1,8,True,4.6868815422058105	247	health,lin,ERM,2,0.0,5,True,0.8574385415387005
171	health,mlp,AF,2,0.1,9,True,4.517419338226318	248	health,lin,ERM,2,0.0,6,True,0.5467518897496327
172	health,mlp,AF,2,0.2,0,True,4.394152641296387	249	health,lin,ERM,2,0.0,7,True,0.665408573976689
173	health,mlp,AF,2,0.2,1,True,1.2017030715942383	250	health,lin,ERM,2,0.0,8,True,0.2177330934524654
174	health,mlp,AF,2,0.2,2,True,4.303710460662842	251	health,lin,ERM,2,0.0,9,True,2.3579908462420525
175	health,mlp,AF,2,0.2,3,True,3.971803665161133	252	health,lin,ERM,2,0.1,0,True,0.17327320480765962
176	health,mlp,AF,2,0.2,4,True,3.635038375854492	253	health,lin,ERM,2,0.1,1,True,1.8289011948466347
177	health,mlp,AF,2,0.2,5,True,2.6649506092071533	254	health,lin,ERM,2,0.1,2,True,0.5256126852308041
178	health,mlp,AF,2,0.2,6,True,5.655788421630859	255	health,lin,ERM,2,0.1,3,True,0.38693286229953283
179	health,mlp,AF,2,0.2,7,True,0.34340187907218933	256	health,lin,ERM,2,0.1,4,True,0.8719336025223833
180	health,mlp,AF,2,0.2,8,True,4.704601287841797	257	health,lin,ERM,2,0.1,5,True,0.9744750323565178
181	health,mlp,AF,2,0.2,9,True,4.650392055511475	258	health,lin,ERM,2,0.1,6,True,0.6637883805674499
182	health,lin,ERM,0,0.0,0,True,0.24817375910864556	259	health,lin,ERM,2,0.1,7,True,0.7824450647945063
183	health,lin,ERM,0,0.0,1,True,0.25525109281411407	260	health,lin,ERM,2,0.1,8,True,0.33476958427028264
184	health,lin,ERM,0,0.0,2,True,1.1881473831940028	261	health,lin,ERM,2,0.1,9,True,2.4750273370598697
185	health,lin,ERM,0,0.0,3,True,2.3542826193516215	262	health,lin,ERM,2,0.2,0,True,0.2903096956254768
186	health,lin,ERM,0,0.0,4,True,1.2289800680688459	263	health,lin,ERM,2,0.2,1,True,1.945937685664452
187	health,lin,ERM,0,0.0,5,True,1.339760725244602	264	health,lin,ERM,2,0.2,2,True,0.6426488760486213
188	health,lin,ERM,0,0.0,6,True,2.3099731253447677	265	health,lin,ERM,2,0.2,3,True,0.5039693531173501
189	health,lin,ERM,0,0.0,7,True,1.7316668221010194	266	health,lin,ERM,2,0.2,4,True,0.9889700933402005
190	health,lin,ERM,0,0.0,8,True,1.3908651939074284	267	health,lin,ERM,2,0.2,5,True,1.091511523174335
191	health,lin,ERM,0,0.0,9,True,1.4392796496285514	268	health,lin,ERM,2,0.2,6,True,0.7808248713852672
192	health,lin,ERM,0,0.1,0,True,0.8009490990781871	269	health,lin,ERM,2,0.2,7,True,0.8994815556123235
193	health,lin,ERM,0,0.1,1,True,0.9652588724751465	270	health,lin,ERM,2,0.2,8,True,0.45180607508809995
194	health,lin,ERM,0,0.1,2,True,0.9107660074809173	271	health,lin,ERM,2,0.2,9,True,2.592063827877687
195	health,lin,ERM,0,0.1,3,True,2.3406677954809383	272	health,mlp,ERM,0,0.0,0,True,0.09999999403953552
196	health,lin,ERM,0,0.1,4,True,1.3595109112283565	273	health,mlp,ERM,0,0.0,1,True,1.1588484048843384
197	health,lin,ERM,0,0.1,5,True,1.4940954924996346	274	health,mlp,ERM,0,0.0,2,False,inf
198	health,lin,ERM,0,0.1,6,True,0.8588585592751913	275	health,mlp,ERM,0,0.0,3,False,inf
199	health,lin,ERM,0,0.1,7,True,0.6920265862777982	276	health,mlp,ERM,0,0.0,4,True,0.09999999403953552
200	health,lin,ERM,0,0.1,8,True,0.16530141673098547	277	health,mlp,ERM,0,0.0,5,False,inf

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278 health,mlp,ERM,0,0.0,6,True,1.7681208848953247
279 health,mlp,ERM,0,0.0,7,True,0.1756606101989746
280 health,mlp,ERM,0,0.0,8,True,0.09999999403953552
281 health,mlp,ERM,0,0.0,9,True,1.099407434463501
282 health,mlp,ERM,0,0.1,0,True,0.2847887873649597
283 health,mlp,ERM,0,0.1,1,True,1.350301742553711
284 health,mlp,ERM,0,0.1,2,False,inf
285 health,mlp,ERM,0,0.1,3,False,inf
286 health,mlp,ERM,0,0.1,4,True,0.17709362506866455
287 health,mlp,ERM,0,0.1,5,True,1.4368488788604736
288 health,mlp,ERM,0,0.1,6,True,1.783553123474121
289 health,mlp,ERM,0,0.1,7,True,0.3221847414970398
290 health,mlp,ERM,0,0.1,8,True,0.14391285181045532
291 health,mlp,ERM,0,0.1,9,True,1.2745985984802246
292 health,mlp,ERM,0,0.2,0,True,0.2927534878253937
293 health,mlp,ERM,0,0.2,1,True,1.420407772064209
294 health,mlp,ERM,0,0.2,2,False,inf
295 health,mlp,ERM,0,0.2,3,True,1.6530849933624268
296 health,mlp,ERM,0,0.2,4,True,0.37585678696632385
297 health,mlp,ERM,0,0.2,5,True,1.0841124057769775
298 health,mlp,ERM,0,0.2,6,True,2.038994312286377
299 health,mlp,ERM,0,0.2,7,True,0.4549943208694458
300 health,mlp,ERM,0,0.2,8,True,0.09999996423721313
301 health,mlp,ERM,0,0.2,9,True,0.543687105178833
302 health,mlp,ERM,1,0.0,0,True,0.6265113949775696
303 health,mlp,ERM,1,0.0,1,True,0.5598059892654419
304 health,mlp,ERM,1,0.0,2,True,4.995126724243164
305 health,mlp,ERM,1,0.0,3,True,0.8848893046379089
306 health,mlp,ERM,1,0.0,4,True,0.9069631099700928
307 health,mlp,ERM,1,0.0,5,True,6.042341232299805
308 health,mlp,ERM,1,0.0,6,True,0.9130632877349854
309 health,mlp,ERM,1,0.0,7,True,0.42502132058143616
310 health,mlp,ERM,1,0.0,8,True,0.09999999403953552
311 health,mlp,ERM,1,0.0,9,True,0.3435572385787964
312 health,mlp,ERM,1,0.1,0,True,0.7597363591194153
313 health,mlp,ERM,1,0.1,1,True,0.7501630187034607
314 health,mlp,ERM,1,0.1,2,True,4.815957069396973
315 health,mlp,ERM,1,0.1,3,True,1.1189303398132324
316 health,mlp,ERM,1,0.1,4,True,0.8854197263717651
317 health,mlp,ERM,1,0.1,5,True,6.365862846374512
318 health,mlp,ERM,1,0.1,6,True,0.8871881365776062
319 health,mlp,ERM,1,0.1,7,True,0.5466513633728027
320 health,mlp,ERM,1,0.1,8,True,0.09999998658895493
321 health,mlp,ERM,1,0.1,9,True,0.35792168974876404
322 health,mlp,ERM,1,0.2,0,True,0.8752454519271851
323 health,mlp,ERM,1,0.2,1,True,0.7518577575683594
324 health,mlp,ERM,1,0.2,2,True,4.760556697845459
325 health,mlp,ERM,1,0.2,3,True,1.0518792867660522
326 health,mlp,ERM,1,0.2,4,True,0.9736133813858032
327 health,mlp,ERM,1,0.2,5,True,2.644326686859131
328 health,mlp,ERM,1,0.2,6,True,0.7649006843566895
329 health,mlp,ERM,1,0.2,7,True,0.6719211935997009
330 health,mlp,ERM,1,0.2,8,True,0.09999998658895493
331 health,mlp,ERM,1,0.2,9,True,0.40259477496147156
332 health,mlp,ERM,2,0.0,0,True,1.6526018381118774
333 health,mlp,ERM,2,0.0,1,True,1.0587971210479736
334 health,mlp,ERM,2,0.0,2,True,0.871553897857666
335 health,mlp,ERM,2,0.0,3,True,1.5454106330871582
336 health,mlp,ERM,2,0.0,4,True,0.09999999403953552
337 health,mlp,ERM,2,0.0,5,True,4.139216899871826
338 health,mlp,ERM,2,0.0,6,True,1.2884514331817627
339 health,mlp,ERM,2,0.0,7,True,1.023694634437561
340 health,mlp,ERM,2,0.0,8,True,0.09999997913837433
341 health,mlp,ERM,2,0.0,9,False,inf
342 health,mlp,ERM,2,0.1,0,True,2.3038556575775146
343 health,mlp,ERM,2,0.1,1,True,0.48094290494918823
344 health,mlp,ERM,2,0.1,2,True,0.9778098464012146
345 health,mlp,ERM,2,0.1,3,True,1.8084425926208496
346 health,mlp,ERM,2,0.1,4,True,0.19984257221221924
347 health,mlp,ERM,2,0.1,5,True,4.787795066833496
348 health,mlp,ERM,2,0.1,6,True,1.3899121284484863
349 health,mlp,ERM,2,0.1,7,True,1.2289860248565674
350 health,mlp,ERM,2,0.1,8,True,0.291856586933136
351 health,mlp,ERM,2,0.1,9,False,inf
352 health,mlp,ERM,2,0.2,0,False,inf
353 health,mlp,ERM,2,0.2,1,True,0.4565989375114441
354 health,mlp,ERM,2,0.2,2,True,1.0854618549346924

```

```

355 health,mlp,ERM,2,0.2,3,True,1.8083579540252686
356 health,mlp,ERM,2,0.2,4,False,inf
357 health,mlp,ERM,2,0.2,5,True,1.6818499565124512
358 health,mlp,ERM,2,0.2,6,True,1.5481600761413574
359 health,mlp,ERM,2,0.2,7,True,1.1980092525482178
360 health,mlp,ERM,2,0.2,8,True,0.37811192870140076
361 health,mlp,ERM,2,0.2,9,True,1.961012840270996

```

APPENDIX I AUTO-GENERATED ACTION PROFILE CSV

Listing 5. Feature-wise action diagnostics CSV

```

1 model,trainer,config,epsilon,seed,feature,
  mean_abs_action_all,mean_abs_action_valid,
  nonzero_rate_all,nonzero_rate_valid,actionable
2 lin,AF,LIN-AF,0.1,0,age,0.0,0.0,0.0,0.0,0
3 lin,AF,LIN-AF,0.1,0,insulin
  ,0.26181564489063913,0.26181564489063913,0.2,0.2,1
4 lin,AF,LIN-AF,0.1,0,blood_glucose,0.0,0.0,0.0,0.0,1
5 lin,AF,LIN-AF,0.1,0,blood_pressure,0.0,0.0,0.0,0.0,0
6 lin,ERM,LIN-ERM,0.1,0,age,0.0,0.0,0.0,0.0,0
7 lin,ERM,LIN-ERM,0.1,0,insulin
  ,0.4521024343304031,0.4521024343304031,0.6,0.6,1
8 lin,ERM,LIN-ERM,0.1,0,blood_glucose
  ,0.0,0.0,0.0,0.0,1
9 lin,ERM,LIN-ERM,0.1,0,blood_pressure
  ,0.0,0.0,0.0,0.0,0
10 mlp,AF,MLP-AF,0.1,0,age,0.0,0.0,0.0,0.0,0
11 mlp,AF,MLP-AF,0.1,0,insulin
  ,0.24029699489474296,0.3003712436184287,0.5,0.625,1
12 mlp,AF,MLP-AF,0.1,0,blood_glucose
  ,0.14958224296569825,0.1869778037071228,0.1,0.125,1
13 mlp,AF,MLP-AF,0.1,0,blood_pressure,0.0,0.0,0.0,0.0,0
14 mlp,ERM,MLP-ERM,0.1,0,age,0.0,0.0,0.0,0.0,0
15 mlp,ERM,MLP-ERM,0.1,0,insulin
  ,0.02044838070869446,0.02272042300966051,0.2,0.2222222222
16 mlp,ERM,MLP-ERM,0.1,0,blood_glucose
  ,0.0870448887348175,0.09671654303868611,0.1,0.1111111111
17 mlp,ERM,MLP-ERM,0.1,0,blood_pressure
  ,0.0,0.0,0.0,0.0,0

```

APPENDIX J AUTO-GENERATED ACTION INSTANCE STATS CSV

Listing 6. Per-instance action vectors and norms CSV

```

1 model,trainer,config,epsilon,seed,instance_id,valid,
  l0_nonzero,l1_norm,l2_norm,cost,action_age,
  action_insulin,action_blood_glucose,
  action_blood_pressure
2 lin,AF,LIN-AF,0.1,0,0,True
  ,0,0.0,0.0,0.0,0.0,0.0,0.0,0.0
3 lin,AF,LIN-AF,0.1,0,1,True
  ,1,0.912671422200381,0.912671422200381,0.912671422200381,0.
4 lin,AF,LIN-AF,0.1,0,2,True
  ,1,1.710092677680237,1.710092677680237,1.710092677680237,0.
5 lin,AF,LIN-AF,0.1,0,3,True
  ,1,1.049107052640722,1.049107052640722,1.049107052640722,0.
6 lin,AF,LIN-AF,0.1,0,4,True
  ,0,0.0,0.0,0.0,0.0,0.0,0.0,0.0
7 lin,AF,LIN-AF,0.1,0,5,True
  ,1,0.04245187920182977,0.04245187920182977,0.04245187920182
8 lin,AF,LIN-AF,0.1,0,6,True
  ,0,0.0,0.0,0.0,0.0,0.0,0.0,0.0

```

9	lin,AF,LIN-AF,0.1,0,7,True ,0,0.0,0.0,0.0,0.0,0.0,0.0,0.0		
10	lin,AF,LIN-AF,0.1,0,8,True ,1,1.3021861189993753,1.3021861189993753,1.3021861189993753,0.0,1.3021861189993753,0.0,0.0	APPENDIX K	
11	lin,AF,LIN-AF,0.1,0,9,True ,0,0.0,0.0,0.0,0.0,0.0,0.0,0.0	AUTO-GENERATED SPARSITY SUMMARY CSV	
12	lin,ERM,LIN-ERM,0.1,0,0,True ,0,0.0,0.0,0.0,0.0,0.0,0.0,0.0	Listing 7. Valid recourse sparsity/cost summary CSV	
13	lin,ERM,LIN-ERM,0.1,0,1,True ,0,0.0,0.0,0.0,0.0,0.0,0.0,0.0	1 model,trainer,config,epsilon,seed,valid_rate, mean_l0_valid,std_l0_valid,mean_l1_valid, std_l1_valid,mean_l2_valid,std_l2_valid	
14	lin,ERM,LIN-ERM,0.1,0,2,True ,1,0.8165668077686034,0.8165668077686034,0.8165668077686034,0.1,0.1,0.5,0.5,0.5016509150722545,0.6355286101893015,0.5	2 lin,AF,LIN-AF ,0.1,0,1.0,0.5,0.5,0.5016509150722545,0.6355286101893015,0.5	
15	lin,ERM,LIN-ERM,0.1,0,3,True ,1,0.8582558826695555,0.8582558826695555,0.8582558826695555,0.1,0.1,0.5,0.5,0.4356022358201116,0.5010741804045753,0.5	3 lin,ERM,LIN-ERM ,0.1,0,1.0,0.5,0.5,0.4356022358201116,0.5010741804045753,0.5	
16	lin,ERM,LIN-ERM,0.1,0,4,True ,1,0.3168366177055238,0.3168366177055238,0.3168366177055238,0.1,0,0.8,0.625,0.6959705453537527,0.4191463515162468,0.5	4 mlp,AF,MLP-AF ,0.1,0,0.8,0.625,0.6959705453537527,0.4191463515162468,0.5	
17	lin,ERM,LIN-ERM,0.1,0,5,True ,0,0.0,0.0,0.0,0.0,0.0,0.0,0.0	5 mlp,ERM,MLP-ERM ,0.1,0,0.5,0.6,0.8,0.06774903079494832,0.10126549888492282,0.5	
18	lin,ERM,LIN-ERM,0.1,0,6,True ,1,1.4160299277944228,1.4160299277944228,1.4160299277944228,1.4160299277944228,1.4160299277944228,1.4160299277944228,1.4160299277944228,1.4160299277944228		
19	lin,ERM,LIN-ERM,0.1,0,7,True ,1,0.9483331222630108,0.9483331222630108,0.9483331222630108,0.9483331222630108,0.9483331222630108,0.9483331222630108,0.9483331222630108,0.9483331222630108	APPENDIX L	
20	lin,ERM,LIN-ERM,0.1,0,8,True ,0,0.0,0.0,0.0,0.0,0.0,0.0,0.0	AUTO-GENERATED BOOTSTRAP SUMMARY CSV	
21	lin,ERM,LIN-ERM,0.1,0,9,True ,0,0.0,0.0,0.0,0.0,0.0,0.0,0.0	Listing 8. Bootstrap confidence interval summary CSV	
22	mlp,AF,MLP-AF,0.1,0,0,False,0,0.0,0.0,inf ,0.0,0.0,0.0,0.0	1 model,trainer,config,epsilon,valid_rate_mean, valid_rate_ci_low,valid_rate_ci_high, valid_cost_mean,valid_cost_ci_low, valid_cost_ci_high,n_rows	
23	mlp,AF,MLP-AF,0.1,0,1,True ,1,0.630301833152771,0.630301833152771,0.630301833152771,0.630301833152771,0.630301833152771,0.630301833152771,0.630301833152771,0.630301833152771	2 lin,AF,LIN-AF ,0.0,1.0,1.0,1.0,0.7012748778796839,0.5062638203282346,0.91	
24	mlp,AF,MLP-AF,0.1,0,2,True ,0,0.0,0.0,0.0,0.0,0.0,0.0,0.0	3 lin,AF,LIN-AF ,0.1,1.0,1.0,1.0,0.823484637148043,0.6173001966002503,1.030	
25	mlp,AF,MLP-AF,0.1,0,3,True ,0,0.0,0.0,0.0,0.0,0.0,0.0,0.0	4 lin,AF,LIN-AF ,0.2,1.0,1.0,1.0,0.9456943964164021,0.7429863056628437,1.16	
26	mlp,AF,MLP-AF,0.1,0,4,False,0,0.0,0.0,inf ,0.0,0.0,0.0,0.0	lin,ERM,LIN-ERM ,0.0,1.0,1.0,1.0,1.0352807148190328,0.795456950585435,1.273	
27	mlp,AF,MLP-AF,0.1,0,5,True ,1,0.2453588843345642,0.2453588843345642,0.2453588843345642,0.2453588843345642,0.2453588843345642,0.2453588843345642,0.2453588843345642,0.2453588843345642	lin,ERM,LIN-ERM ,0.1,1.0,1.0,1.0,1.0044488235328917,0.7995385802997136,1.22	
28	mlp,AF,MLP-AF,0.1,0,6,True ,2,1.7315754890441895,1.2251203467080083,1.7315754890441895,1.2251203467080083,1.7315754890441895,1.2251203467080083,1.7315754890441895,1.2251203467080083	7 lin,ERM,LIN-ERM ,0.2,1.0,1.0,1.0,1.120386324703241,0.9017732550292862,1.360	
29	mlp,AF,MLP-AF,0.1,0,7,True ,0,0.0,0.0,0.0,0.0,0.0,0.0,0.0	8 mlp,AF,MLP-AF ,0.0,0.9666666666666667,0.9,1.0,1.810989550732333,1.2662813	
30	mlp,AF,MLP-AF,0.1,0,8,True ,0,0.0,0.0,0.0,0.0,0.0,0.0,0.0	9 mlp,AF,MLP-AF ,0.1,0.9666666666666667,0.9,1.0,1.9862833922279293,1.434618	
31	mlp,AF,MLP-AF,0.1,0,9,True ,1,0.7459346055984497,0.7459346055984497,0.7459346055984497,0.7459346055984497,0.7459346055984497,0.7459346055984497,0.7459346055984497,0.7459346055984497	10 mlp,AF,MLP-AF ,0.2,0.9333333333333333,0.8333333333333334,1.0,2.0226513711	
32	mlp,ERM,MLP-ERM,0.1,0,0,True ,0,0.0,0.0,0.0,0.0,0.0,0.0,0.0	11 mlp,ERM,MLP-ERM ,0.0,0.8666666666666667,0.7333333333333333,0.9666666666666667	
33	mlp,ERM,MLP-ERM,0.1,0,1,True ,0,0.0,0.0,0.0,0.0,0.0,0.0,0.0	12 mlp,ERM,MLP-ERM ,0.1,0.9,0.8,1.0,1.3640946765188817,0.8771141729972981,1.94	
34	mlp,ERM,MLP-ERM,0.1,0,2,False,0,0.0,0.0,inf ,0.0,0.0,0.0,0.0	13 mlp,ERM,MLP-ERM ,0.2,0.9,0.8,1.0,1.151049994484142,0.8237234620736629,1.529	
35	mlp,ERM,MLP-ERM,0.1,0,3,False,0,0.0,0.0,inf ,0.0,0.0,0.0,0.0		
36	mlp,ERM,MLP-ERM,0.1,0,4,False,0,0.0,0.0,inf ,0.0,0.0,0.0,0.0		
37	mlp,ERM,MLP-ERM,0.1,0,5,False,0,0.0,0.0,inf ,0.0,0.0,0.0,0.0		
38	mlp,ERM,MLP-ERM,0.1,0,6,False,0,0.0,0.0,inf ,0.0,0.0,0.0,0.0		
39	mlp,ERM,MLP-ERM,0.1,0,7,True ,0,0.0,0.0,0.0,0.0,0.0,0.0,0.0		
40	mlp,ERM,MLP-ERM,0.1,0,8,True ,1,0.07758744060993195,0.07758744060993195,0.07758744060993195,0.07758744060993195,0.07758744060993195,0.07758744060993195,0.07758744060993195,0.07758744060993195	ACKNOWLEDGMENT	
41	mlp,ERM,MLP-ERM,0.1,0,9,True ,2,0.26115771336480975,0.25923200853642037,0.26115771336480975,0.25923200853642037,0.26115771336480975,0.25923200853642037,0.26115771336480975,0.25923200853642037	This submission was prepared for Trusted Artificial Intelligence coursework, under Dr. Mostafa Tavakoli pour	9111091792583,0.0

REFERENCES

- [1] B. Ustun, A. Spangher, and Y. Liu, “Actionable recourse in linear classification,” in *Proceedings of the Conference on Fairness, Accountability, and Transparency*, 2019.
- [2] J. Pearl, *Causality: Models, Reasoning, and Inference*. Cambridge University Press, 2009.
- [3] A.-H. Karimi, G. Barthe, B. Balle, and I. Valera, “Algorithmic recourse: from counterfactual explanations to interventions,” in *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*, 2021.
- [4] R. K. Mothilal, A. Sharma, and C. Tan, “Explaining machine learning classifiers through diverse counterfactual explanations,” *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency*, 2020.
- [5] A.-H. Karimi, B. Schölkopf, and I. Valera, “Algorithmic recourse under imperfect causal knowledge: A probabilistic approach,” in *Advances in Neural Information Processing Systems*, 2020.