Paper Summary

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Title: Towards User Guided Actionable Recourse

Authors: Jayanth Yetukuri, Ian Hardy, Yang Liu

DOI: https://doi.org/10.1145/3600211.3604708

Year: 2023

Publication Type: Conference

Discipline/Domain: Artificial Intelligence / Human-Centered Computing

Subdomain/Topic: Actionable Recourse, User Preferences in ML Explanations

Eligibility: Eligible

Overall Relevance Score: 92

Operationalization Score: 95

Contains Definition of Actionability: Yes (implicit, user-preference-centered)

Contains Systematic Features/Dimensions: Yes

Contains Explainability: Yes

Contains Interpretability: Partial

Contains Framework/Model: Yes (UP-AR optimization & workflow)

Operationalization Present: Yes

Primary Methodology: Conceptual with empirical evaluation

Study Context: Actionable recourse in ML decision-making across domains such as credit, hiring, insuran

Geographic/Institutional Context: University of California, Santa Cruz; U.S.

Target Users/Stakeholders: End-users affected by ML decisions (e.g., loan applicants), ML system desig

Primary Contribution Type: Method/Framework Proposal with Empirical Validation

CL: Yes — “communicating in terms of preference scores… improves the explainability of a recourse gen

CR: Yes — “actionability… centered explicitly around individual preferences… may not necessarily be eq

FE: Yes — “feasible action set… actionable by Alice” (p.1)

TI: Partial — timeliness not a primary dimension, but operational efficiency is addressed

EX: Yes — “preference scores… improves the explainability of a recourse generation mechanism” (p.1)

GA: Yes — goal alignment with user’s own constraints and desires (p.1–2)

Reason if Not Eligible: n/a

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Towards User Guided Actionable Recourse

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Subdomain/Topic:

Actionable Recourse, User Preferences in ML Explanations

Contextual Background:

The paper addresses the challenge of making ML-generated recourse actionable for individuals adversel

Geographic/Institutional Context:

University of California, Santa Cruz; U.S.

Target Users/Stakeholders:

End-users denied desired outcomes by ML systems; system designers and policymakers interested in tru

Primary Methodology:

Conceptual framework and algorithm development with empirical evaluation across multiple datasets.

Primary Contribution Type:

Method/Framework Proposal with Empirical Validation

General Summary of the Paper

The authors introduce **User Preferred Actionable Recourse (UP-AR)**, a novel method for generating a

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Eligibility

Eligible for inclusion: **Yes**

How Actionability is Understood

Actionability is defined implicitly as the **viability of taking a suggested action** within the constraints and

> “Actionability… is centered explicitly around individual preferences, and similar recourses… may not ne

> “AR aims to provide… a feasible action set which is both actionable by Alice and… as low-cost [as poss

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What Makes Something Actionable

- Alignment with individual user constraints and desires (hard and soft rules)

- Ability to operationalize within user’s own cost and effort parameters

- Feasibility in practice (e.g., avoiding impossible or undesirable feature changes)

- Explainability of why the action is suggested and how it fits user preferences

- Personalization beyond general feasibility rules

How Actionability is Achieved / Operationalized

- **Framework/Approach Name:** User Preferred Actionable Recourse (UP-AR)

- **Methods/Levers:** Gradient-based iterative optimization weighted by user preference scores; tempera

- **Operational Steps / Workflow:**

  1. Elicit three types of preferences (scoring, bounding, ranking) from the user.

  2. Embed these as constraints in optimization.

  3. Generate candidate recourse via stochastic gradient-based updates informed by user preference-wei

  4. Apply redundancy and cost correction to finalize recourse.

- **Data & Measures:** Percentile shift cost function; pRMSE to evaluate preference adherence; tradition

- **Implementation Context:** Credit lending, income prediction, recidivism risk prediction.

> “We start by enabling Alice to provide three types of user preferences… We embed them into an optimi

> “The proposed method minimizes the cost of a recourse weighted by Γ■ for all actionable features” (p.3

Dimensions and Attributes of Actionability (Authors’ Perspective)

- **CL (Clarity):** Yes — user preference scores increase explainability (p.1)

- **CR (Contextual Relevance):** Yes — recourse tailored to individual user profile (p.1–2)

- **FE (Feasibility):** Yes — constraints ensure recommendations are viable for that user (p.1–3)

- **TI (Timeliness):** Partial — efficiency in generation is discussed, but timeliness as a decision-making

- **EX (Explainability):** Yes — preference-based reasoning improves explainability (p.1)

- **GA (Goal Alignment):** Yes — recourse aligned with user’s stated objectives (p.1–2)

- **Other Dimensions:** Diversity only as secondary contrast to preference tailoring

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Theoretical or Conceptual Foundations

- Builds on **Actionable Recourse (AR)** as per Ustun et al. (2019)

- Local feasibility concept from Mahajan et al. (2019)

- Preference elicitation parallels human-in-the-loop approaches (De Toni et al., 2022)

- Optimization inspired by gradient-based adversarial example generation

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Indicators or Metrics for Actionability

- pRMSE between desired and achieved feature cost proportions

- Constraint violations (lower is better)

- Redundancy (steps that don't affect outcome)

- Sparsity (number of features changed)

- Proximity (l2 distance from original point)

Barriers and Enablers to Actionability

- **Barriers:** Ignoring user-specific constraints; reliance on universal cost functions; high redundancy; ex

- **Enablers:** Explicit preference capture; flexible optimization accommodating hard/soft constraints; cos

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Relation to Existing Literature

The authors note most AR literature focuses on universal feasibility and cost minimization, sometimes ad

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Summary

This paper reframes **actionability** in ML recourse as inherently **user-specific** and **preference-drive

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Scores

- **Overall Relevance Score:** 92 — Strong, explicit integration of user-centered definition of actionability

- **Operationalization Score:** 95 — Detailed algorithm and empirical workflow directly aimed at achievin

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Supporting Quotes from the Paper

- "Actionability… is centered explicitly around individual preferences…" (p.1)

- "We start by enabling Alice to provide three types of user preferences… embed them into an optimizatio

- "Communicating in terms of preference scores… improves the explainability of a recourse generation m

- "The proposed method minimizes the cost of a recourse weighted by Γ■ for all actionable features" (p.3

Actionability References to Other Papers

- Ustun et al. (2019) — Actionable Recourse in Linear Classification

- Mahajan et al. (2019) — Local Feasibility

- De Toni et al. (2022) — Human-in-the-loop preference elicitation

- Wachter et al. (2017) — Counterfactual Explanations

- Poyiadzi et al. (2020) — FACE method