Iterative machine learning algorithms used to power recommender systems often change people’s preferences by trying to learn them. Further a recommender can better predict what a user will do by making its users more predictable. Some preference changes on the part of the user are self-induced and desired whether the recommender caused them or not. This paper proposes that solutions to preference manipulation in recommender systems must take into account certain meta-preferences (preferences over another preference) in order to respect the autonomy of the user and not be manipulative.

Additional Key Words and Phrases: Meta Preferences, Manipulation, Recommender Systems

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1 INTRODUCTION

Recommender systems try to predict a user’s preferences in order to offer them a personalized selection of options on a given platform. In economics, preference is often defined as a choice between alternative options originating from utility theory. However, this is an operational definition - a definition for a concept which cannot be directly measured. In truth the term preferences is unconscionably vague. Sometimes it covers the user’s beliefs about the world, their hedonic state or mood or their psychometric attributes. All this in addition to an ordering over alternatives in the spirit of its use in utility theory. Now is not the space to separate all these meanings out, but we are aware that a finer grain definition and taxonomy of preferences is desirable. In line with Franklin et al. [2022b], we conceptually define preferences as any explicit, conscious, and reflective or implicit, unconscious, and automatic mental process that brings about a sense of liking or disliking for something. In practice we note that in research and practice, the term preferences is also used to describe a person’s beliefs or knowledge about the world. The existing discussion of preference manipulation often therefore also concerns the manipulation of beliefs. The provision of a finer set of definitions and a taxonomy is a project for the future. For now the vagueness is tolerable.

In this paper we discuss this a potential solution to preference manipulation in recommender systems; namely, learning meta-preferences - people’s preferences over their own preferences. After identifying the source of preference manipulation and introducing meta preferences this paper propose a requirement to solutions which claim to solve the recommender preference manipulation problem, itself an example of auto-induced distributional shift [Krueger et al. 2020].

2 THE PROBLEM OF BEHAVIOUR AND PREFERENCE MANIPULATION IN RECOMMENDER SYSTEMS

Machine learning (ML) can be used to understand user preferences in order to improve recommender systems. Recommender systems gather stated or revealed preferences in the attempt to better predict what a user will do in the future. In economics, a choice of one option over another indicates a preference for it. This is an example of a ‘revealed preference’ – the preference is assumed to be revealed through the agent’s actions [Samuelson 1938]. ’Stated preferences’ are the preferences of an agent that are elicited by directly asking the agent [Kroes and Sheldon 1988]. Both approaches have their drawbacks. People are not be fully rational [Dhami and Sunstein 2022], they may not accurately report their preferences [Sunstein 2018], and they may be influenced by how questions are worded [Špecián 2019]. Behaviour is restricted by the choices open to a user at any time, potentially confounding analysis.

Over and above this, human preferences change over time and can be manipulated [Franklin et al. 2022b]. If an iterative machine learning algorithm is used, it becomes difficult to know whether the recommender system has learned about its users, whether the users have changed, or whether the system has taught users to behave in ways that maximizes the objective function [Ashton and Franklin 2022]. This becomes more difficult because of the bidirectional causal relationship between behaviour and preferences Ariely and Norton [2008]. A recommender system trained to maximise user ‘engagement’ has an incentive to change users’ preferences [Everitt et al. 2021]. A recommender can better do its job in predicting what its users will do if it makes its users more predictable [Russell 2019]. This has been shown in simulation by, amongst others, Evans and Kasirzadeh [2021] and Jiang et al. [2019].

3 INITIAL SOLUTIONS TO THE MANIPULATION PROBLEM

Various potential solutions have been put forward to solve the preference manipulation problem. Everitt et al. [2021] show that a recommender serving content to a user using a preference set based on the counterfactual world where the user had not interacted with the system removes the preference manipulative incentive. Carroll et al. [2022] penalise a recommender system for shifting the preferences of a user ‘unnaturally’. The reasoning is promising - penalising recommender systems for the wrong kind of shifts - but the execution is lacking. They pragmatically define natural preference shifts as those that a user would undergo if presented with a random slate of recommendations. [Farquhar et al. 2022] examine the causal path that may cause preference change and prevent the algorithm from using elements on that path as a means to an end - ie shifting preferences to suit its preferences.

We argue that these solutions are unsatisfactory because they fail to take into account the user’s meta-preferences. Some users like


| Meta Preference | Preferences |
|-----------------|-------------|
| Likes           | Dislikes    |
| Dislikes        |             |
| ‘Righteous-pleasure’ | ‘Righteous-hatred’ |
| ‘Guilty-pleasure’   | ‘Guilty-hatred’   |

Table 1. Meta-preferences are preferences over preferences

the preference shift that content engenders. Here the recommender is a cause of their preference shift but it is a welcome one. The only way to disentangle welcome shifts from unwelcome or even manipulative ones is to learn about the user’s meta preferences. Causal analysis alone won’t cut it.

4 META PREFERENCES

A meta preference is a preference of another preference and is itself a preference [Franklin et al. 2022b]. To give a concrete example, someone might enjoy a certain film, but simultaneously wish that they didn’t. This we might characterise as a guilty pleasure (see Table 1). Similarly they might dislike exercise and dislike that about themselves (a guilty chore or hatred perhaps). Further, they may also like that they like certain things (righteous-pleasure) and like that the dislike other things (righteous-hatred).

Although meta-preferences can be changed, they are more stable than preferences [Pettigrew 2019], which can change from moment to moment. Some have called these more fundamental changes to a persons meta-preferences Transformative Experiences [Paul 2014; Pettigrew 2020]. The presence of a fast-food restaurant may change one’s preference for what they want to eat right now, but will not change their meta preference towards being healthy. An chronic illness, on the other hand, can be a Transformative Experience that influences a person’s meta-preferences [Carel et al. 2017; Hole and Selman 2020]. Do meta preferences thus allow better recommendations? Do people who like something as a guilty pleasure like different things from someone who just flat out likes the thing?

A different view of meta-preferences is to consider their intertemporal nature. That is to say the preference over the their preference in the future - Conative Preferences. Consider one of the author’s dislike for mushrooms and their desire that they liked them more, because they feel that they are missing out on mycological cuisine. An example of this comes from Free Traits - people’s ability to adopt new personally traits for a given situation they are in [Little 2008]. People often adopt free traits for the purpose of fulfilling a personal project to the best of their ability [Little and Joseph 2017]. Little [2017] who developed Free Trait Theory often gives the autobiographic example of an introverted professor adopting extraversion to achieve his personal project of being a good teacher.

The difference between meta-preferences and conative-preferences seems slight but the possession of a guilty pleasure does not imply that the owner wants to to not have it in the future. The manipulation of preferences concerns caused changes of user preferences, so its study will involve conative-preferences to some degree. If a recommender system were to cause some change in user preferences against that user’s conative-preferences, then that would be a bad outcome. Additionally if a recommender system were to deny someone from satisfying their conative-preferences that would also be bad, potentially trapping users in an unwanted preference state.

5 PREFERENCE-CHANGE PREFERENCES

As well as having a preference as to how their preferences evolve in the future, people will also have a preference about what causal mechanism alters their preferences. Previous research has termed these Preference-Change Preferences [Franklin et al. 2022b]. Self-development could be characterised as a voluntary or self-initiated change in preferences through the collection of knowledge or experience. Generally people have a positive preference towards the process. Manipulation might be described as the deliberate change of preferences by an external party. There are those who require manipulation to be hidden from the manipulated [Susser et al. 2018] but we side with the account of [Benn and Lazar 2022] who do not require this. It is possible to be manipulated even if we are aware of it and how it works. Unlike self-development, manipulation is not done with the permission of the target and is autonomy reducing. Ethically, algorithmic manipulation is dubious [Christian 2022], and occasionally illegal as the EU AI Act details [Franklin et al. 2022a]. The ideal recommender system would respect the user’s preference-change preferences.

6 PREFERENCE-CHANGE CONSENT

If a recommender system were to understand how any recommendation were to change the preferences of a user, it would be able to ask that user, before serving it, whether the user was comfortable with that. By doing so, the recommender would be able to respect the meta-preferences of the user.

Looking around in the real world, one can see examples of this in the film classification system which warns viewers about the content of films, before they watch them. Whilst they do not say what effect a film will have on a viewer, by warning the viewer about elements of the film, they will often make it possible for a viewer to avoid films that elicit certain reactions.

Would this end manipulation by recommender systems? Unfortunately not. Whilst preference manipulation will be made harder if a recommender system obeys a users meta-preferences, it might not make it impossible. The recommender could aim to change the user’s meta-preferences and thereby legitimately change their preferences. The ease of achieving this is unknown and a suitable question for further investigation.

Recommender engines could additionally tell a user what they currently think a user’s preferences are. Such an interaction would be possible with the use of example based Explainable Artificial Intelligence (XAI) methods [van der Waa et al. 2021]. Example-based explanations provide users historical situations (e.g., films that they have watched) to the current situation (e.g., film that is being recommended). This would serve as a meta preference elicitation method. A user could choose whether or not the learnt preference does in fact match their preferences more broadly - their meta-preferences. For example a recommender system may learn from a users’ behaviour that they have a preference for 1970s musicals. A participant can disclose whether or not this does match their preferences.

1Arbitrary high levels of meta preference are allowable therefore.
If not the recommender engine can treat it as an anomaly rather than as a new drastic change in the users preference.

7 CONCLUSION
This paper outlines the the preference manipulation problem in recommender systems and briefly introduces meta-preferences. It is our position that by learning users’ meta-preferences, a recommender system can better align with what users want, while being autonomy respecting. Preventing a recommender from causing a user’s preferences is not desirable because in many situations a user does consent to them being changed by the recommender. Human-in-the-loop architectures have been used to learn from users’ preferences [Christiano et al. 2017] and with work can be extended to aid in what we propose.

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REFERENCES
Dan Ariely and Michael I. Norton. 2008. How actions create – not just reveal – preferences. Trends in Cognitive Sciences 12, 1 (Jan. 2008), 13–16. https://doi.org/10.1016/j.tics.2007.10.008

Hal Ashton and Matija Franklin. 2022. The problem of behaviour and preference manipulation in AI systems. In CEUR Workshop Proceedings. Vol. 3087. CEUR Workshop Proceedings.

Claire Benn and Seth Lazar. 2022. What’s Wrong with Automated Influence. Canadian Journal of Philosophy 52, 1 (Jan. 2022), 125–148. https://doi.org/10.1017/can.2021.23

Havi Carel, Richard Pettigrew, and Ian James Kidd. 2017. Illness as transformative experience. The Lancet 388 (2017).

Nicah Carroll, Anca Dragan, Stuart Russell, and Dylan Hadfield-Menell. 2022. Estimating and Penalizing Induced Preference Shifts in Recommender Systems. Proceedings of machine learning research 162 (2022), 2686–2708.

Paul F Christiano, Jan Leike, Tom Brown, Májlan Martie, Shane Legg, and Dario Amodei. 2017. Deep reinforcement learning from human preferences. Advances in neural information processing systems 30 (2017).

Thomas Christiano. 2022. Algorithms, Manipulation, and Democracy. Canadian Journal of Philosophy 52, 1 (Jan. 2022), 109–124. https://doi.org/10.1017/can.2021.29

Sanjit Dhami and Cass R Sunstein. 2022. Bounded Rationality: Heuristics, Judgment, and Public Policy. MIT Press.

Charles Evans and Atoosa Kasirzadeh. 2021. User Tampering in Reinforcement Learning Recommender Systems. arXiv:2109.04083 [cs] (Sept. 2021). http://arxiv.org/abs/2109.04083 arXiv:2109.04083

Tom Everitt, Ryan Carey, Eric Langlois, Pedro A. Ortega, and Shane Legg. 2021. Agent Incentives: A Causal Perspective. In AAAI Conference on Artificial Intelligence. http://arxiv.org/abs/2102.01685

Sebastian Farquhar, Ryan Carey, and Tom Everitt. 2022. Path-Specific Objectives for Safer Agent Incentives. Proceedings of the AAAI Conference on Artificial Intelligence 36, 9 (June 2022), 9529–9538. https://doi.org/10.1609/aaai.v36i9.21186

Matija Franklin, Hal Ashton, Rebecca Gorman, and Stuart Armstrong. 2022a. Missing Mechanisms of Manipulation in the EU AI Act. The International FLAIRS Conference Proceedings 35 (May 2022). https://doi.org/10.32473/FLAIRS.v35i130723

Matija Franklin, Hal Ashton, Rebecca Gorman, and Stuart Armstrong. 2022b. Recognising the importance of preference change: A call for a coordinated multidisciplinary research effort in the age of AI. arXiv preprint arXiv:2205.10525 (2022).

Barnaby Hole and Lucy Selman. 2020. Illness as transformative experience: Implications of philosophy for advance care planning. Journal of Pain and Symptom Management 59, 1 (2020), 172–177.

Ray Jiang, Silvia Chiappa, Tor Lattimore, Andrius György, and Pushmeet Kohli. 2019. Degenerate Feedback Loops in Recommender Systems. Proceedings of the 2019 AAAI/ACM Conference on AI, Ethics, and Society (Jan. 2019), 383–390. https://doi.org/10.1145/3306618.3314288 arXiv:1902.10730

Eric P Kroes and Robert J Sheldon. 1988. Stated preference methods: an introduction. Journal of transport economics and policy (1988), 11–25.

David Krueger, Tegan Maharaj, and Jan Leike. 2020. Hidden Incentives for Auto-Induced Distributional Shift. arXiv:2009.09153 [cs, stat] (Sept. 2020). http://arxiv.org/abs/2009.09153 arXiv:2009.09153

Brian R Little. 2008. Personal projects and free traits: Personality and motivation reconsidered. Social and Personality Psychology Compass 2, 3 (2008), 1235–1254.

Brian R Little. 2017. Prompt and circumstance: The generative contexts of personal projects analysis. In Personal Project Pursuit Goals, Action, and Human Flourishing. Psychology Press, 3–50.

Brian R Little and Maryann F Joseph. 2017. 14 Personal Projects and Free Traits: Mutable Selves and Well Beings. In Personal Project Pursuit Goals, Action, and Human Flourishing. Psychology Press, 375–400.

Laurie Ann Paul. 2014. Transformative experience. OUP Oxford.

Richard Pettigrew. 2019. Choosing for changing selves. Oxford University Press.

Richard Pettigrew. 2020. Transformative Experience and the Knowledge Norms for Action. Becoming someone new: Essays on transformative experience, choice, and change (2020), 100.

Stuart J. Russell. 2019. Human compatible: artificial intelligence and the problem of control. Allen Lane, an imprint of Penguin Books, London.

Paul A Samuelson. 1938. A note on the pure theory of consumer’s behaviour. Economica 5, 17 (1938), 61–71.

Petr Specian. 2019. The Precarious Case of the True Preferences. Society 56, 3 (2019), 267–272.

Cass R Sunstein. 2018. Unleashed. Social Research: An International Quarterly 85, 1 (2018), 73–92.

Daniel Susser, Beate Roesler, and Helen F. Nissenbaum. 2018. Online Manipulation: Hidden Influences in a Digital World. SSRN Electronic Journal (2018). https://doi.org/10.2139/ssrn.3368066

Jasper van der Waa, Elisabeth Nieuwburg, Anita Cremers, and Mark Neerincx. 2021. Evaluating XAI: A comparison of rule-based and example-based explanations. Artificial Intelligence 291 (2021), 103484.