Equality of Learning Opportunity in Personalized Recommendations

Mirko Marras · Ludovico Boratto · Guilherme Ramos · Gianni Fenu

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Abstract Online educational platforms are promising to play a primary role in mediating the success of individuals’ careers. Hence, while building underlying content recommendation services, it becomes essential to ensure that learners are provided with equal learning opportunities, according to the platform values, context, and pedagogy. Even though the importance of creating equality of learning opportunities has been well investigated in traditional institutions, how it can be operationalized scalably in online learning ecosystems through recommender systems is still under-explored. In this paper, we formalize principles, that aim to model a range of learning opportunity properties in recommendations, and a metric that combines them to quantify the equality of learning opportunities among learners. Then, we envision a scenario wherein platform owners seek to guarantee that the generated recommendations meet each principle, to a certain degree, for all learners, constrained to their individual preferences. Under this view, we provide observations on learning opportunities in a real-world online dataset, highlighting inequalities among learners. To mitigate this effect, we propose a post-processing approach that balances personalization and learning opportunity equality in recommendations. Experiments on a large-scale dataset demonstrate that our approach leads to higher equality of learning opportunity, with a small loss in personalization.

Keywords Education, Recommender Systems, Fairness, Bias, Ethics.
1 Introduction

Learning experience selection is the driver of curriculum development and, consequently, a vital activity towards shaping individuals’ knowledge and competencies (Talla, 2012; Druzhinina et al., 2018). The term learning experience generally refers to interactions in courses, programs, or other situations where learning takes place, including traditional and non-traditional settings (Girvan, 2018). Notable examples of the latter, with a tangible impact on individual experiences, are online course platforms, such as Coursera and Udemy. The proliferation of initiatives and the increasing adoption of these platforms have required to investigate automated mechanisms of personalized experience selection, depending on the platform or institution’s values, context, pedagogy, and needs (Rieckmann, 2018).

One aspect receiving special attention to support the learning experience selection on these platforms is the ranking of courses based on the predicted relevance for learners. In this view, recommender systems are being deployed to suggest courses that accommodate individual interests and needs (Kulkarni et al., 2020). Such recommended courses can be viewed as a set of learning opportunities being subjected to the attention of a learner. Though optimizing recommendations for learners’ interests has been seen for years as the goal, it does not consider other principles that curriculum-design experts manually inspect in traditional situations to shape learning opportunities (e.g., validity, variety) (Talla, 2012; Druzhinina et al., 2018). Depending on the context, recommendations thus need to meet a trade-off between the interests of learners and the principles of the platform or institution, producing learners with a well-rounded range of learning experiences (Abdollahpour et al., 2020).

Under this scenario, ensuring equality among learners according to the opportunities proposed by a recommender system becomes essential, as the suggested courses potentially translate to educational gains or losses. By extension, education significantly influences an individuals life chances in terms of job market success, and these opportunities should not be undermined by certain arbitrary decisions emphasized by a recommender system. While equality of learning opportunity has been well investigated in traditional educational settings (Meyer, 2016), how it can be operationalized scalably in online learning ecosystems through recommender systems is still under-explored. These systems learn patterns from historical data with biases in terms of imbalances, which may be emphasized in the results suggested to learners (Boratto et al., 2019). We are thus concerned that this effect may lead to learners being offered low-quality learning opportunities concerning the principles pursued by platform owners. Fig. 1 gives a schematic depiction of this phenomenon. For this reason, it is imperative to mitigate inequalities, retaining personalization.

1 https://www.coursera.org/
2 https://www.udemy.com/
3 Please note that the figures in this manuscript are best seen in color.
Fig. 1: Example of Inequality in Learning Opportunities. We consider two users, $u_i$ and $u_j$ (first line). The mid-line shows us that the users interacted with similar resources in terms of quality (star:high; square:low), validity (light-blue:old; dark-blue:fresh), and affordability level (1:low; 2:mid; 3:high). However, if we consider ranked lists provided by a collaborative algorithm to those two users (bottom line), $u_i$’s recommendation list consists of mostly fresh, high-quality, and affordable resources, while $u_j$’s recommendations focus on obsolete, low-quality, and expensive resource.

With this study, we propose the concept of equality of learning opportunities in personalized recommendations. To this end, we characterize those proposed by ten recommendation algorithms to learners included in a real-world online course dataset, as a function of seven principles built upon knowledge and curriculum literature (e.g., validity, quality). Then, we envision a scenario wherein platform owners seek to guarantee that these principles are met for all the users, to a certain degree, when generating recommendations according to the learner’s interests. Our experiments shed light on the importance of measuring and mitigating inequalities of opportunities based on the properties held by the suggested courses.

The contribution is four-fold:

– Operational: we formalize principles that aim to model a range of learning opportunity properties, and define a metric that combines them to quantify the equality of learning opportunities among learners in a recommendation.
– Social: based on the sample principles, we provide observations and insights on learning opportunities in recommendations, leveraging a dataset that includes more than 40K learners who interacted with over 30K courses.
– Technical: we propose a post-processing recommendation approach that aims to balance personalization and learning opportunity equality, making it possible to optimize different combinations of principles.
– Ethical: we evaluate the proposed supporting approach on a real-world public dataset, and show that it leads to higher equality of learning opportunities among learners, with a minimum loss in personalization.

The remaining of this paper is structured as follows. Section 2 contains related work. Section 3 introduces principles and metrics, and Section 4 presents the explorative experiments. Then, Section 5 describes and evaluates the framework that reduces inequality of learning opportunities among learners. Finally, Section 6 presents our concluding remarks and highlights future research.
2 Related Work

This research relies on literature from both the educational recommender system and the fairness and ethics in recommendation communities.

2.1 Recommender Systems in Education

Research on learning personalization is getting more and more critical with the increasing use of digital environments, such as learning object repositories, learning management systems, and devices for mobile learning (Ureten et al., 2017). This advancement has made data collection an inherent process of delivering content to learners, especially with the appearance of Massive Open Online Courses (MOOCs) (Zheng et al., 2015) and the Learning Analytics (LA) (Greller and Drachsler, 2012) field.

Recommending resources within courses is the most common task in the literature. New tasks have recently appeared as online education evolves, starting to consider recommendations of entire online courses. For instance, Blumichitr et al. (2017) introduced a collaborative-filtering recommender system based on the similarity of the learners’ interactions over courses. Segal et al. (2019) combined collaborative filtering with majority voting methods. They constructed a ranking for each learner by aggregating the rankings of similar learners using their performance on common questions (e.g., grades, number of retries). Similarly, Elbadrawy and Karypis (2016); Jing and Tang (2017) investigated how learner and course academic features influence enrollments, and they combined those two aspects to design rankings based on collaborative filtering, matrix factorization, and popularity-based methods.

Other approaches, such as Bridges et al. (2018), leveraged a graph-based method for course recommendation using grade and enrollment data. Course enrolment sequences were analyzed to create a personalized course transition graph that balances learner’s grades, expected improvement, and course popularity. Likewise, Zhang et al. (2019a) captured latent relationships among courses as a graph, mined learners’ past course performance data, and recommended top-\(k\) courses most helpful to a given learner. Recently, Rao et al. (2019); Pardos and Jiang (2020) capitalized on content-based features and enrolment patterns to create top-\(k\) recommendations and considered beyond-accuracy metrics to seek specific goals of the platform (e.g., serendipity). Their approach presented novel courses still relevant to learners’ interests.

Our approach differs from prior work in two main ways. First, existing works were mostly optimized for accuracy under a prediction of ratings, grades, or the number of enrolments, while our approach can be tuned on more ranking-related properties directly measurable on the ranked lists. Our strategy allows controlling how learning opportunities vary, going beyond accuracy (e.g., validity or quality of courses). Second, even though existing grade-based recommender systems integrated some similar concepts, such as learnability, combining them with other properties and controlling equality with respect to
platform owners’ principles appears impractical. We thus devise a novel post-processing mechanism that can be applied to existing recommenders in order to arrange how they meet the principles of platform owners, across learners.

2.2 Ethics in Recommender Systems

Concepts regarding fairness, accountability, transparency, and ethics are receiving more and more attention in the recommender system community (Barocas et al., 2017; Ramos et al., 2020). Specifically, fairness across final users deals with ensuring users who belong to different protected classes (group-based) or are similar at the individual level (individual-based) receive recommendations with the same quality. Existing works propose fairness notions and pre-, in-, or post-processing approaches.

Group-based fairness usually requires that the protected groups are treated similarly to the advantaged groups or the population as a whole. Zhu et al. (2018) addressed this goal with an approach that identifies and removes from tensors all gender information about users. Similarly, Rastegarpanah et al. (2019) generated artificial data to balance group representations, and minimized the difference between groups in terms of mean squared error. Conversely, Yao and Huang (2017) proposed metrics related to population imbalance (i.e., a class of users characterized by a sensitive attribute being the minority) and observation bias (i.e., a class of users who produced fewer ratings than their counterpart). Then, such metrics were added to the matrix factorization loss function to be minimized.

Under a similar scenario, Beutel et al. (2019) built a pairwise regularization that penalizes the model if its ability to predict which item was clicked is better for one group than the other. Mitigating unfairness with post-processing was addressed by Edizel et al. (2020). They defined a list as \( \epsilon \)-fair if the predictability of a sensitive feature of the user receiving the recommendations is lower than a value \( \epsilon \). To achieve that goal, while ensuring \( \epsilon \)-fairness, a re-ranking algorithm minimizes the loss in accuracy.

Rather than focusing on groups, our study cares more about learners, individually. Individual fairness is more fine-grained than group-notion fairness, as it imposes restrictions on the treatment for each pair of individuals. Related works by Biega et al. (2018); Lahoti et al. (2019a); Singh and Joachims (2019) formulated individual fairness notions (i.e., similar users have similar outcomes), while we slightly generalize this concept by targeting the same outcome (i.e., consistency to target principles of the platform) for all learners; we do not rely on any notion of similarity across learners’ based on how learning opportunity principles were met by learners in past interactions, as it could even emphasize existing inequality among learners. Indeed, prior works aimed to achieve equality from the side of item providers, while we focus on the user who receives recommendations. They solved an integer linear program, while we adopt maximum marginal relevance. Lastly, existing methods...
require to tune internal parameters to meet the target properties, while we try to directly set the target values for the considered properties as parameters.

3 Problem Formulation

In this section, we formalize the main recommendation concepts, the considered principles we explore in our study, and two new metrics that respectively shape consistency and equality of learning opportunity among learners.

3.1 Preliminaries

Given a set of learners $U$ and a set of educational resources $I$, we assume that learners expressed their interest for a subset of resources in $I$. The collected feedback from learner-resource interactions can be abstracted to a set of pairs $(u, i)$ implicitly obtained from user activity, or triplets $(u, i, \text{rating})$ explicitly provided by learners, shortly denoted by $R_{u,i}$. We denote the learner-resource feedback matrix by $R \in \mathbb{R}^{M \times N_m}$ where $R_{u,i} > 0$ indicates that learner $u$ interacted with resource $i$, and $R_{u,i} = 0$ otherwise. Furthermore, we denote the set of resources that learners $u \in U$ interacted with by $I_u = \{ i \in I : R_{u,i} > 0 \}$.

We will further assume that each resource $i \in I$ is represented by a $m$-dimensional feature vector $F_i = (f_1, \ldots, f_m)$ over a set of features $F = \{ F_{i,1}, F_{i,2}, \ldots, F_{i,m} \}$. Each dimension $F_j$ can be viewed as a set of values or labels describing a feature of a resource $i$, $f_{i,j} \in F_j$ for $j = 1, \ldots, m$.

In our experiments, we considered five features, i.e., instructional level (discrete), resource category (discrete), last update timestamp (discrete date-time), number of enrolled learners (continuous), and price (continuous). Furthermore, we assume that each resource $i \in I$ is composed by a set of assets $L_i$. Each $l_{i,j} \in L_i$ has a type $t_{i,j} \in T$. In our study, we considered $T = \{ \text{Video}, \text{Article}, \text{Ebook}, \text{Podcast} \}$, due to their popularity and their availability in the public datasets.

We assume that a recommender estimates relevance for unobserved entries in $R$ for a given learner, and uses them for ranking resources. It can be abstracted as learning $\tilde{R}_{u,i} \in [0,1]$, which represents the predicted relevance of resource $i$ for learner $u$. Given a certain learner $u$, resources $i \in I \setminus I_u$ are ranked by decreasing $\tilde{R}_{u,i}$, and top-$k$, with $k \in \mathbb{N}$ and $k > 0$, resources are recommended. Finally, we denote the set of $k \in \mathbb{N}$ resources recommended to user $u$ by $\tilde{I}_u$.

3.2 Sample Learning Opportunity Principles

Shaping learning opportunities in traditional scenarios, such as schools or universities, has been often conducted by humans using a range of principles coming from education-related literature (e.g., significance, self-sufficiency, validity, interest, utility, learnability, feasibility) (Talla 2012; Druzhinina et al.).
The inspection of such principles is usually based on textual guidelines, and the translation into numerical indicators, when available, is subject to the specificity of the platform or institution. In other cases, only qualitative inspections are conducted.

By capitalizing on prior education-related work and the peculiarities of the online context, this study envisions a scenario wherein a range of sample curriculum-design principles are embedded into the recommender system’s logic. Platform owners are enabled to control to what extent the list of resources recommended to learners meets each principle. The range of principles is formalized through numerical indicators that can be automatically computed for a recommended list of resources. While they are assumed to be relevant and interesting, the proposed principles are just examples of how common text-based principles could be operationalized to be manipulated into the recommender’s system logic. The framework we built upon them can be easily adapted to any principle, according to the values of the specific platform.

Formally, we consider a set $\mathcal{C}$ of functions $c_{\tilde{I}_u}(\cdot): I^k \rightarrow [0, 1]$. Each one receives a set of $k$ resources $I^k$ and returns a value indicating how much the set of resources meets the corresponding principle. We consider the following:

**Familiarity** is a peculiar principle in the context of learner-centered education. Learners learn best if the subject matter is meaningful to them, and it is assumed that it becomes meaningful if they are familiar with that subject. In our scenario, familiarity is associated with the category of the resources in a list. Specifically, a list is familiar for a user w.r.t. a given category $g \in G$, if it contains a number of elements of that category proportional to the previous interactions of the user with $g$. Given a course feature $F_1 \in \mathcal{N}$ related to an integer-encoded representation of the category $g \in G$ of a resource $4$, which is assumed to be given, we consider two distributions:

1. $x(g|u)$: the distribution over categories $G$ of the set of resources $I_u$ user $u$ interacted with in the past, defined as $x(g|u) = |I^g_u|/|I_u|$;
2. $y(g|u)$: the distribution over categories $G$ of the set of learning opportunities $\tilde{I}_u$ recommended to learner $u$, defined as $y(g|u) = |\tilde{I}^g_u|/|\tilde{I}_u|$;

where $I^g_u$ and $\tilde{I}^g_u$ represent the set of resources belonging to category $g$ the learner $u$ attended and the recommender system proposed, respectively. Then, we define the familiarity of $\tilde{I}_u$ for a learner $u$ as the inverse of the Hellinger distance across $x(G|u)$ and $y(G|u)$. Specifically:

$$c_{\tilde{I}_u}(1) = 1 - H(x(G|u), y(G|u))$$

where $c_{\tilde{I}_u}(1) = 1$ if $x_u$ and $y_u$ are perfectly balanced, and the highest familiarity is achieved. Conversely, the minimum familiarity 0 is achieved when $x_u$ assigns probability 0 to every event that $y_u$ assigns a positive probability (or

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4 In the dataset we used, COCO, categories are mapped on multiple levels (specifically, 2). In our study, we considered the first level category of a resource.
vice versa). In the latter situation, the recommender suggests resources in the opposite direction with respect to the user’s most familiar categories.

This principle is related to the concept of calibrated recommendations, which aim to reflect the various interests of a user in the recommended list with their appropriate proportions (Steck, 2018). They used the Kullback-Leibler divergence, which is non-symmetric, unbounded, and computationally unstable. The Hellinger distance is symmetric and bounded in the range [0, 1].

Validity refers to the freshness of the recommended subject matter to make sure that it is not obsolete. Curriculum-design experts usually seek to follow current trends and carefully consider the validity of a curriculum; otherwise, the learning opportunity becomes obsolete. Given a course feature $F_2 \in \mathcal{N}$ representing the last time a resource has been updated and the opening time of the platform, denoted as $T_o$, we define the validity of a set of learning opportunities $I_u$ at the current time $T_c$ as follows:

$$c_{I_u}(2) = \frac{1}{|I_u|} \sum_{i \in I_u} \frac{T_c - f_{2,i}}{T_c - T_o}$$

where values close to 0 mean that the learning opportunities are obsolete, while values close to 1 correspond to mostly fresh opportunities in $I_u$.

Learnability implies that the subject matter must be within the schema of the learners and their experiences. Our scenario includes this concept to ensure that subjects are presented at diverse instructional levels to maximize the possibility that a learner will find an opportunity coherent with his/her capability. Given a course feature $F_3 \in \mathcal{N}$ representing the instructional level of a resource, we define the learnability in $I_u$ as:

$$c_{I_u}(3) = 1 - GINI \left( \frac{|I_u|}{|\tilde{I}_u|} \forall f_3 \in F_3 \right)$$

where $c_{I_u}(3)$ is the inverse of Gini inequality index over the representations of all the instructional levels in $I_u$, and $\tilde{I}_u$ is the set of resources in $I_u$ with instructional level $f_3$. Values close to 0 imply large inequality among levels, while high balance is obtained with values close to 1.

Variety takes into account that learners are different and learn in different ways based on their interests and ability. Our scenario assumes that varied asset types may be provided to help learners comprehend the subject from various perspectives. To this end, we consider that each resource $j \in \tilde{I}_u$ is composed by a set of assets $L_j$ and that the list of asset types in a resource $j$ is denoted by $T_j = (t_l \in T : \forall l \in L_j)$. Then, we define the variety of the types in $\tilde{I}_u$ as:

$$c_{I_u}(4) = \frac{1}{|I_u|} \sum_{i \in I_u} \left| \frac{T_i}{T} \right|$$

where values close to 0 mean that the learning opportunities are focused on few asset types, while asset types greatly vary for values close to 1.
**Quality** is generally connected with how a resource is perceived, when it is used in the individual learning situation and with relation to whom. The perceived quality for learners is influenced by the individual ability and personality while critically assessing her/his own learning experiences within those situations. This principle is operationalized by leveraging the value of ratings usually released by learners online. Given a learner-resource feedback’s matrix $R$ as previously defined and that the platform allows for ratings between $F_{5_{\text{min}}}$ to $F_{5_{\text{max}}}$, we define the quality of a set $\tilde{I}_u$ as follows:

$$c_{\tilde{I}_u}(5) = \frac{1}{|\tilde{I}_u|} \sum_{i \in \tilde{I}_u} \sum_{u \in U_i} \frac{F_{5_{\text{max}}} - R_{u,i}}{F_{5_{\text{max}}} - F_{5_{\text{min}}}}$$

(5)

where values close to 0 mean that the learning opportunities are of low quality, while values close to 1 are measured for high-quality opportunities.

**Manageability** is conceived concerning the size of the learners’ class, where the offered learning opportunities will happen. Having a large number of learners, the instructor may work harder to combat student passivity and encourage participation, as learners feel an increasing sense of anonymity. Hence, operationalizing this principle can be relevant to offer opportunities under smaller and more controlled classes. In our scenario, given a course feature $F_6 \in \mathcal{N}$ representing the number of enrolled learners in a course and that the platform allows for classes from $F_{6_{\text{min}}}$ to $F_{6_{\text{max}}}$ learners, we define the manageability in a set of learning opportunities $\tilde{I}_u$ as follows:

$$c_{\tilde{I}_u}(6) = 1 - \frac{1}{|\tilde{I}_u|} \sum_{i \in \tilde{I}_u} \frac{F_{6_{\text{max}}} - f_{6,i}}{F_{6_{\text{max}}} - F_{6_{\text{min}}}}$$

(6)

where values close to 0 mean that the learning opportunities include barely small classes, while values close to 1 refer to very large classes.

**Affordability** aims to control the degree of openness for the proposed learning opportunities, in terms of enrolment fees. Resources may be free or charged, and, in the latter case, it should be considered how much they cost. Our scenario seeks to control how the learning opportunities cover a wide range of fee ranges. Given a course feature $F_7 \in \mathcal{R}$ representing the course enrollment fee and that the platform allows for courses with a cost between $F_{7_{\text{min}}}$ and $F_{7_{\text{max}}}$, we define the affordability of a set of learning opportunities $\tilde{I}_u$ as follows:

$$c_{\tilde{I}_u}(7) = \frac{1}{|\tilde{I}_u|} \sum_{i \in \tilde{I}_u} \frac{F_{7_{\text{max}}} - f_{7,i}}{F_{7_{\text{max}}} - F_{7_{\text{min}}}}$$

(7)

where values close to 0 mean that the learning opportunities are all free of charge, while values close to 1 correspond to expensive opportunities in $\tilde{I}_u$. 
3.3 Learning Opportunity Equality Definition

To formalize the equality of learning opportunities, we first need to define how much the list recommended to each learner met the goals sought by platform owners concerning the aforementioned principles. Our work proposes to formalize the latter concept as the similarity between the degree all principles are met into the recommended list and the principles degree targeted by the platform owners. The higher the similarity, the more the principles are met. We resorted to such a notion locally on each ranked list, so that it will be possible to optimize it via a re-ranking function. For the ranked list $\tilde{I}_u$ of learner $u$, we assume platform owners seek to ensure a targeted degree for each principle $c \in C$:

$$p_u(m) \in [0, 1], \forall m \in \{0, \cdots, |C| - 1\}$$  (8)

When a recommender computes the top-$k$ resources $\tilde{I}_u$ to be suggested to user $u \in U$, we define the degree principles are met for resources in $\tilde{I}_u$ as:

$$q_{\tilde{I}_u}(m) = c_{\tilde{I}_u}(m) \in [0, 1], \forall m \in \{0, \cdots, |C| - 1\}$$  (9)

where the value corresponding to each principle $q_{\tilde{I}_u}(m)$ is computed by applying the formulas formalized in the previous section.

For the ranked list of a user $u$, the principles targeted by platform owners are met if the values in $p_u$ and $q_{\tilde{I}_u}$ are aligned with each other. Hence, to support the principles’ goals targeted by platform owners, we compare the vectors $p_u$ and $q_{\tilde{I}_u}$. We define the Consistency between target principles and how much principles are achieved in recommendations by the complement of the Manhattan (M) distance, which is symmetric and bounded.

$$\text{Consistency}(u|w) = 1 - M(p_u, q_{\tilde{I}_u}|w) = 1 - \frac{1}{|\tilde{I}|} \sum_{i=1}^{|\tilde{I}|} w_i \left|p_u[i] - q_{\tilde{I}_u}[i]\right|$$  (10)

$$\text{Consistency}(U|w) = \frac{1}{|U|} \sum_{u \in U} \text{Consistency}(p_u, q_{\tilde{I}_u}|w)$$  (11)

where $w$ is a vector of size $|C|$; the element $w_i$ is the weight assigned to the principle $i$, between 0 and 1. Consistency is 1 if $p_u$ and $q_{\tilde{I}_u}$ are perfectly balanced, meaning that the principles pursued by platform owners are met. Conversely, the lowest Consistency 0 is achieved when $p_u$ assigns value 0 to every principle that $q_{\tilde{I}_u}$ assigns value 1 (or vice versa), so that the distributions are completely unbalanced. In the latter situation, the recommender suggests resources in the opposite direction with respect to the platform owners’ goals.

We formalize the Equality as the complement of the Gini index (Conceição and Galbraith (2000)) over the consistencies across learners. The Gini index

$$\text{Equality}(U|w) = 1 - \sum_{u \in U} \text{Consistency}(p_u, q_{\tilde{I}_u}|w)$$
ranges between 0 and 1, with higher values representing distributions with high inequality. It is used as:

\[
\text{Equality}(U|w) = 1 - \text{GINI} \left( \{\text{Consistency}(u|w) \mid \forall u \in U \} \right)
\]  \hspace{1cm} (12)

where a value of 0 represents the largest inequality across consistencies, and a value of 1 means that the recommender systems are perfect equal across learners. Differently from Lahoti et al. (2019b); Biega et al. (2018), we count as a positive effect when learners achieve high consistency in recommendations, regardless of the consistency in their past interactions. Thus, the ideal recommender system would be the one that (i) achieves the higher consistency between the principles pursued by the platform and those measured in the recommendations, (ii) keeps it equal over the learners’ population, and (iii) retains individual interests of learners.

4 Exploratory Analysis

To illustrate the trade-off between learners’ interests and the considered principles and further emphasize the value of our analytical modeling and re-ranking, we characterize the learning opportunities proposed by ten algorithms to learners of a real-world educational dataset as a function of the proposed principles.

4.1 Data

We analyze data from the educational context, exploring the role of the proposed principles in recommendations. We remark that the experimentation is made difficult because there are very few large-scale educational datasets. To the best of our knowledge, COCO (Dessi et al., 2018) is the widest educational dataset with all the attributes required to model the proposed principles and with enough data to assess performance significantly. Collected from an online course platform, it includes 43,045 courses and 4,123,127 learners who gave 6,564,870 ratings. Other educational datasets proposed by Feng et al. (2019); Zhang et al. (2019b); Qiu et al. (2016) mostly include \((\text{learner}, \text{course}, \text{rating})\) samples needed in traditional recommendation scenarios.

4.2 Recommendation Algorithms and Protocols

We considered ten different methods, and we investigated the recommendations they generated. Two of them are baseline recommenders, and the other eight are state-of-the-art algorithms, chosen due to their performance, wide adoption, and core applicability in learning contexts (Kulkarni et al., 2020).

- Non-Personalized: Random and TopPopular.
- Neighbor-based: UserKNN and ItemKNN (Sarwar et al., 2001).
– Matrix-Factorized: GMF (He et al., 2017), NeuMF (He et al., 2017).
– Graph: P3-Alpha (Cooper et al., 2014) and RP3-Beta (Paudel et al., 2016).
– Content: ItemKNN-CB (Lops et al., 2011).
– Hybrid: CoupledCF (Zhang et al., 2018).

Based on hyperparameter tuning, UserKNN and ItemKNN relied on cosine metric and 100 neighbors. GMF and NeuMF used 10 factors and were trained on 4 negative samples per positive instance. P3-Alpha was executed with 0.8 alpha and 200 neighbors, while RP3-Beta adopted 0.6 alpha, 0.3 beta, and 200 neighbors. ItemKNN-CB mapped course descriptions to Term-Frequency Inverse-Document Frequency (TF-IDF) features. The TF-IDF features of courses into the user’s profile were averaged, and their cosine similarity with the TF-IDF features of other courses is used during ranking. CoupledCF embedded user-item associations, the user tendency to interact with each category of courses, and the category of the course in the current user-item pair.

To be as close as possible to a real scenario, we used a fixed-timestamp split (Campos et al., 2014). The basic idea is to choose a single timestamp that represents the moment in which test learners are on the platform waiting.

![Data Statistics](image-url)

Fig. 2: Data Statistics. Characteristics of the real-world dataset relevant to the learning opportunity principles proposed by this paper: course popularity, rating values, last update timestamp, thematic category, instructional level, asset types (V:Video; A:Article; E:Ebook; P:Podcast), prices, number of enrolments per course, and average rating per course. Subfigure captions specify the feature and the interested principle as <Feature>:<principle>.
ing for recommendations. Their past corresponds to the training set, and the performance is evaluated with data coming from their future. In this work, we select the splitting timestamp 2017-06-08, which maximizes the number of learners involved in the evaluation by setting two constraints: the training set must keep at least 4 ratings per user, and the test set must contain at least 1 rating. This split led to 43,021 learners, 24,321 courses, and 529,857 interactions (Figure 2). Normalized Discounted Cumulative Gain (NDCG) \cite{Jarvelin:2002} is used as recommendation effectiveness metric.

4.3 Real-World Observations

We characterize how the proposed principles were met into the lists of courses suggested by the considered algorithms. To this end, we envision a scenario where the platform owners seek to maximize all the stated principles, i.e., \( p_u = 1 \cdot |C| \), \( \forall u \in U \) and give the same maximum weight to all the principles, i.e., \( w_i = 1 \cdot |C| \), \( \forall u \in U \). Three research questions drove our analysis:

1. Does it exist a relation between consistency and equality? If so, which one?
2. Which principles have the largest impact on consistency and equality?
3. Are consistency and equality influenced by the past interactions of learners?

**Disparate Equality.** We applied the recommendation algorithms to all learners, recommending to each learner \( k = 10 \) courses; then we measured global consistency, i.e., how much the target principles were achieved in the recommendations of all learners (Eq. 11), and equality, i.e., how much the consistency achieved by all learners were similar (Eq. 12). Table 1 reports global performance. Higher values indicate that the metric is favored by the corresponding recommender. A first observation we can draw is the following:

**Observation 1.** Recommenders that embed content metadata reduce the disparate equality across learners. When the recommender uses only user-item interactions, the disparate equality is emphasized. This holds regardless of the algorithm’s subfamily.

Though the observation above holds, the values of equality, as a whole, and the mean values of consistency do not reveal much about how consistency brings to equality. We can observe this effect when we plot user consistencies across learners for each algorithm, sorted by increasing order (Figure 3a), especially for the two most effective methods ItemKNN-CB and CoupledCF. We conjecture that their performance might depend on the fact that, in the presence of principles related to the course content, the content-based and hybrid methods may increase those principles and lead to higher consistency. In other words, their equality could be biased by the fact that they capitalize on input information that is related to some principles. While such a situation could happen in some well-rounded cases, it would become generally impractical to arrange the internal logic of an algorithm to accommodate the current
Table 1: **Global Indicators.** Normalized Discounted Cumulative Gain (NDCG), global consistency, and equality produced by different families of recommenders. Italic values highlight the highest value for each metric across algorithms. The highest NDCG is achieved by UserKNN, while the highest consistency and equality was observed for CoupledCF.

| Model     | NDCG   | Consistency | Equality |
|-----------|--------|-------------|----------|
| Random    | 0.000  | 0.000       | 0.000    |
| TopPopular| 0.035  | 0.035       | 0.035    |
| UserKNN   | 0.072  | 0.586       | 0.872    |
| ItemKNN   | 0.021  | 0.756       | 0.795    |
| P3Alpha   | 0.001  | 0.485       | 0.685    |
| RP3Beta   | 0.000  | 0.491       | 0.847    |
| NeuMF     | 0.042  | 0.578       | 0.917    |
| GMF       | 0.013  | 0.572       | 0.706    |
| ItemKNNCB | 0.008  | 0.662       | 0.699    |
| CoupledCF | 0.010  | 0.652       | 0.727    |
| TopPopular| 0.042  | 0.699       | 0.727    |
| UserKNN   | 0.013  | 0.717       | 0.727    |

(a) Consistency distribution. (b) Consistency errors bars. (c) Equality w.r.t. Consistency.

Fig. 3: **Consistency over the Entire Population.** On the left plot, lines represent the consistency distribution over learners, sorted in increasing order. On the center plot, each error bar includes mean (dot), std deviation (black solid line), and min-max values (colored thick line). The right plot highlights the direct relation between consistency and equality.

principles pursued by the platform. To have a more detailed picture, Figure 3b plots the consistency error bars for each algorithm, with mean, standard deviation, minimum, and maximum values. It could be observed that there is a clear link between the magnitude of the mean and of the standard deviation. More precisely, the higher the mean consistency guaranteed by the algorithm is, the lower is the standard deviation across consistency values (Fig. 3c).

**Observation 2.** Recommenders with high consistency lead to higher equality of learning opportunities. Such property is stronger for neural collaborative, content-based, and hybrid recommenders.

Later on, we shed light on the importance of this relation. Specifically, uncovering a link between a metric that requires knowledge about the whole learner population (i.e., equality) and a metric that can be directly optimized on a single ranked list (i.e., consistency), makes it possible to apply a non-NP-Hard re-ranking procedure to solve our task. This suggests to investigate the interplay between the user consistency as a whole, and the consistency within each principle.

**Disparate Principle Targeting.** We investigated further these observations by showing the consistency achieved by each recommendation algorithm over every single principle. For the sake of readability and conciseness, we do not further consider the Random algorithm over the analysis. Figure 4 reports the mean, standard deviation, minimum, and maximum values over each principle on that recommender. For instance, the *coupledcf* plot shows that the
familiarity principle has a mean of 0.80, a standard deviation of ±0.05, and spans the whole range (min: 0.00; max: 1.00). The first observations can be made for the top popular algorithm, whose results reveal that popular courses are mostly fresh (high validity) and of high quality. However, this benefit comes at the price of low familiarity, learnability, variety, and affordability. Considering algorithms that capitalize on course metadata (CoupledCF and ItemKNN-CB), similar patterns can be observed over principles, except on variety and quality. For the latter principles, embedding user-item interactions in CoupledCF made it possible to reduce the min-max gap. Hence, situations

Fig. 4: Algorithm over Principle. For each recommendation algorithm, the corresponding plot reports an error bar for each principle as measured for that algorithm, including mean (dot), std deviation (solid black line), and min-max values (thick colored line).

Fig. 5: Principle over Algorithms. For each principle, the corresponding plot reports an error bar for each algorithm as measured for that algorithm, including mean (dot), std deviation (solid black line), and min-max values (thick colored line).
where few learners experience very high (low) values can be avoided. Other algorithms achieved more stable consistency across principles.

To assess whether certain algorithms favor (run down) a given principle, Figure 5 reports for each principle how it varies over algorithms. It can be observed that familiarity and affordability suffer from high deviations, while more stable values were measured for other principles, over algorithms. We conjecture that the stability observed on quality comes from the highly unbalanced rating value distribution. Indirectly, this effect could come from the fact that learners tend to evaluate courses with high ratings when they decide to rate them. Figure 5 also confirmed this. On principles like affordability, manageability, and learnability, the two mentioned algorithms got lower values.

Observation 3. **Quality, validity, and manageability are guaranteed to high extent by different recommenders, regardless of the family. Familiarity, affordability, learnability, and variety experience low absolute values and substantial deviations over algorithms.**

To further confirm the role of each principle over user consistency, we looked at the correlation between the consistency achieved for a given principle and the user consistency achieved by including all the principles. In Figure 6, we report the results for each principle and algorithm pair. Observed values higher than 0 are expected when the consistency at the principle level is directly related to the high consistency achieved at the user level. Hence, user consistency

![Fig. 6: Principle-Consistency Relation. Heatmap of correlations between the consistency for a given principle and the global consistency computed for each user, over different algorithms. Each value ranges in [-1, +1], and for each principle and algorithm, the Spearman correlation is computed over a distribution of (principle value, user consistency) pairs.](image-url)
tends to be met when that principle is met. Conversely, values lower than 0 result in the opposite behavior. No relation is found when the reported value is close to 0. This allows us to shed light on another observation:

**Observation 4.** **Familiarity, learnability, and affordability are the most influencing principle on the user consistency. This effect is stronger for content-based and hybrid recommenders.**

Most of the observations seen so far are based on the fact that the observed consistency values are averaged over learners. However, it is interesting to ask whether, for two learners with similar past interactions with respect to the considered principles, we should expect a similar consistency. In other terms, it is interesting to ask whether similar learners get similar consistency.

*Past Interaction Influence.* We next take an individual fairness standpoint, i.e., the principle according to which similar individuals should receive a similar treatment. In our setting, for learners, we assume that being similar means having similar consistency in their past interactions. Therefore, we computed

![Consistency in Profile and Recommendation](image1)

*Fig. 7: Consistency in Profile and Recommendation.* The lines show the difference in recommendation consistency over random pairs of learners, with values sorted by increasing difference in consistency in profiles.

![Learners with More (Less) Consistency](image2)

*Fig. 8: Learners with More (Less) Consistency.* For each principle, the corresponding plot reports the mean consistency achieved in recommendations by learners with high consistency in their profile (orange) and low consistency in their profile (blue).
the consistency metric defined in Eq. 10 by substituting the vector $q_{\tilde{I}_u}$ with the vector $q_{I_u}$, so that we can quantify how much the pursued principles were met into the set of past interactions of each learner.

To this end, for all the possible pairs of learners, $u_1$ and $u_2$, we computed the difference in consistency in their profile and in their recommendations. Figure 7 depicts pairs of results by increasing the difference in consistency in profiles. It can be observed that, except for the graph-based P3Alpha and RP3Alpha, a higher similarity in consistency between the profiles results in a higher similarity of consistency over the recommendations. Figure 8 also shows, for each principle and algorithm, the consistency achieved by best and worst learners, according to the aforementioned definition. It is confirmed that familiarity, learnability, variety, and affordability play a crucial role in the consistency at the learner level.

**Observation 5.** Learners who interacted with courses aligned with the principles are likely to receive recommendations that meet those principles. Similar learners in terms of profile consistency receive a similar treatment in terms of recommendation consistency.

With the observations made so far, we conjecture that re-ranking each list of recommendations in order to maximize the considered principles will lead to higher consistency, and, consequently, to higher equality.

5 **Support Framework Definition and Evaluation**

In this section, we describe, evaluate, and discuss our approach to maximize the consistency of a given set of principles in recommendations (Figure 9).

5.1 **Learning Opportunities Equality Control**

To meet the principles pursued by platform owners for each learner and push for equality of opportunities among them, we introduce a recommendation procedure that seeks to maximize the consistency formalized in Eq. 10. Since,
in general, it is hard to plug-in the balancing phase into the internal logic of a recommender system, we propose to re-arrange the recommended lists obtained from a general recommender system. This re-arrange is a common practice in a recommendation, known as re-ranking [Potey and Sinha 2017].

For each learner \( u \in U \), our goal is to determine an optimal set \( I^* \) of \( k \) resources to be recommended to \( u \), so that the principles pursued by the platform owners are met with a minimum loss in recommendation effectiveness. To this end, we capitalize on a maximum marginal relevance [Carbonell and Goldstein 1998] approach, with Eq. 10 as the support metric. The set \( I^* \) is obtained as the solution of the optimization problem:

\[
I^*(u|k, w) = \arg\max_{I \subseteq \mathcal{I}, |I| = k} \left( 1 - \lambda \right) \sum_{i \in I} \tilde{R}_{ui} + \lambda \text{Consistency}(p_u, q_{\mathcal{I}}|w),
\]

where \( q_{\mathcal{I}} \) is \( q \) when the top-\( k \) list includes items \( \mathcal{I} \), and \( \lambda \in [0, 1] \) is a parameter that expresses the trade-off between accuracy and learning opportunity consistency. With \( \lambda = 0 \), we yield the output of the recommender, not taking consistency optimization into account. Conversely, with \( \lambda = 1 \), the output of the recommender is discarded, and we focus on maximizing consistency.

The combinatorial maximization problem in Eq. (13) may be efficiently approximated with a greedy approach with \((1 - 1/e)\) optimality if the objective function of the maximization is submodular. We prove it below.

**Theorem 1** Let \( \text{Consistency}(p, q|w) = 1 - w\|p - q\|_C \), with \( |C| > 0 \) and \( w_i \geq 0 \ \forall i \in \{0, \cdots, |C|\} \), then for any \( \lambda \in [0, 1] \) the function in (13),

\[
f(\mathcal{I}|w) = (1 - \lambda) \sum_{i \in \mathcal{I}} \tilde{R}_{ui} + \lambda \text{Consistency}(p_u, q_{\mathcal{I}}|w),
\]

is submodular.

**Proof** First, since \( \tilde{R}_{ui} > 0 \), it follows that \( f_1(\mathcal{I}|w) = \sum_{i \in \mathcal{I}} \tilde{R}_{ui} \) is a modular function (i.e., hence, also submodular), because it is a sum of positive quantities. Second,

\[
f_2(\mathcal{I}|w) = \text{Consistency}(p_u, q_{\mathcal{I}}) = w\|p_u - q_{\mathcal{I}}\|_C
\]

\[
= \sum_{i=1}^{k} w_i [p_{ui}]_i - [q_{\mathcal{I}}]_i|_C = \sum_{i=1}^{k} x_i,
\]

where \( x_i = w_i [p_{ui}]_i - [q_{\mathcal{I}}]_i|_C > 0 \). Again, \( f_2 \) is modular because it is a sum of positive quantities. Since \( f(\mathcal{I}|w) = (1 - \lambda)f_1(\mathcal{I}|w) + \lambda f_2(\mathcal{I}|w) \), and the convex combination of submodular functions is submodular, \( f \) is submodular.

This greedy approach yields an ordered list of resources, and the resulting list at each step is \((1 - 1/e)\) optimal among the lists of equal size. This property
fits with the real world, where learners may initially see only the first $k$ recommendations, and the remaining items may become visible after scrolling. Our approach also allows controlling more than one learning opportunity principle in the ranked lists, with no constraints on the size of $C$.

5.2 Supporting Scenario and Results

In this section, we explore the impact of controlling consistency and equality of learning opportunities across learners, after applying our procedure to pursue the platform owners’ goals (i.e., maximizing all the principle indicators). It is important to note that we considered the same setup described for the exploratory analysis, including the same datasets (Section 4.1), protocols (Section 4.2), and metrics (Section 3), to answer four research questions:

- RQ1. Which weight setup achieved the best accuracy-equality trade-off?
- RQ2. Which principles have experienced the largest gain in consistency?
- RQ3. Which is the influence of the original relevance score distribution?
- RQ4. How do the recommended lists before and after our approach differ?

**Influence of Weight Setup.** We run experiments to assess (i) the influence of our procedure and the weight-based strategy on accuracy, consistency, and equality, and (ii) the relation between a loss in accuracy and a gain in consistency and equality while applying our procedure. To this end, we envisioned three approaches of principle weight assignment, while applying our procedure:

- **Glob** assigns the same weight to all the principles, for all users. This method would not take into account the level of consistency the recommended list to a given user already achieved and will treat all the principles equally.

- **User** assigns, to a principle, a weight proportional to the consistency gap for that principle concerning the target of the platform, computed during the exploratory analysis. The consistency gap for a principle has been obtained by averaging the individual consistency gaps across users.

- **Pers**, given a user, assigns the weight for a principle by considering only his/her (individual) consistency gap for that principle. Thus, different weights are used along with the user population.

For each model, we run an instance of our re-ranking procedure for each weight assignment strategy, assigning to $\lambda$ a value in $[0.0, 0.25, 0.50, 0.75, 0.99]$.

Results on NDCG, consistency, and equality are shown in Figure 10. Specifically, top-row plots on NDCG highlighted the fact that ItemKNN and ItemKNN-CB experienced the largest loss in NDCG at increasing $\lambda$. The rest of the algorithms showed a more stable pattern on NDCG, even though the NDCG absolute value is significantly lower with respect to the one achieved by ItemKNN and ItemKNN-CB. Throughout the weight assignment strategy, no significant difference was observed for the same algorithm over the three strategies. On the other hand, the weight assignment strategy has an important role in consistency and equality (center and bottom rows). **User** and **Pers** weight setups
made it possible to achieve higher consistency and quality than \texttt{Glob}. It can also be observed that all the algorithms bring the same degree of improvement in consistency while varying $\lambda$. Interestingly, by looking at equality scores, two patterns of improvement were observed. The algorithms from the graph-based, content-based, and hybrid families showed a larger improvement at each value of $\lambda$ with respect to the one achieved by the other families of algorithms.

\textbf{Observation 6.} The considered weight assignment strategies do not differ in terms of impact on NDCG. However, User and Pers lead to consistency and equality values higher than \texttt{Glob}, at the same $\lambda$.

To have a more detailed picture, we analyzed the relation between a loss in NDCG and a gain in consistency and equality. Such a plot plays a key role in a real-world context. While it is the responsibility of scientists to bring forth the discussion about metrics, and possibly to design algorithms to optimize them by turning parameters, it is ultimately up to the stakeholders to select the trade-offs most suitable for their context. Therefore, this kind of plot would support platform owners in deciding the value of $\lambda$ to set up in production in order to achieve the desired trade-off. Figure\[\11\] plots the gain
In consistency (top row) and quality (bottom row) resulting from the degree of loss the platform owners are willing to have. It can be observed that the patterns of consistency and equality within the same weight strategy are related. This observation confirms the results of our exploratory analysis, where we noticed that consistency and equality improvement are directly correlated. This correlation allows us to make another observation.

Observation 7. Applying the Glob weighting strategy results in the largest improvement in equality and consistency, subjected to a given NDCG loss, regardless of the recommendation algorithm.

Influence on Each Principle. In this subsection, we run experiments to assess (i) which principles benefited more from the proposed approach, and (ii) which is the impact of the weight assignment strategy on the consistency of each principle. To answer these questions, for each model, we run an instance of our re-ranking procedure for each weight assignment strategy, varying $\lambda \in \{0.0, 0.25, 0.50, 0.75, 0.99\}$. Then, we computed the consistency of each principle achieved by an algorithm at a given $\lambda$ with a given weight assignment strategy.

Figure 12 reports the impact of our procedure on the considered principle, for different algorithms. Overall, it can be observed that our procedure allows us to improve the consistency overall the principles, except Quality (see Fig. 12c). Such a principle exhibited two main patterns based on the algorithms: quality increased for ItemKNN and RP3Beta, while it decreased for the other algorithms. Interestingly, adding course metadata information into the algorithm (ItemKNN-CB with respect to ItemKNN) overturns the trend in quality. Our approach made it also possible to improve Familiarity, Va-
Fig. 12: Controlled Consistency. Consistency per principle achieved by our procedure under under the Glob weight assignment strategies at various $\lambda$.

Consistency in Familiarity, Validity, Learnability, Variety, Quality, Manageability, and Affordability, which achieved the lowest consistency scores in the exploratory analysis. It follows that platform owners can tune $\lambda$ in order to reach the desired level for a given principle.

Observation 8. Controlling learning opportunity results in higher familiarity, variety, and affordability, while maintaining stable values for the other principles. However, quality may slightly decrease, especially under plain collaborative filtering.

Influence of Relevance Score Distribution. Having observed that the improvement in consistency greatly varies among algorithms, we conjecture that the distribution of relevance scores returned by the original algorithm may influence the feasibility of our approach.

To this end, Figure 13 shows the density of relevance scores along the range $[-1, 1]$. It can be observed that GMF, NeuMF, and ItemKNN-CB produced relevance scores with a high density around zero. Therefore, in our approach, the relevance part may be dominated by the consistency part, regardless of the applied $\lambda$. Consequently, relevance could have a drastic drop even for $\lambda$ values, making it harder to find a good trade-off between accuracy and consistency.
Fig. 13: Relevance Score Distribution. For each algorithm, we compute the density of the user-item relevance scores computed by the original version of the recommender.

This behavior is confirmed by the results previously reported in Figure 11. The NDCG loss compared to the Consistency gain is higher for GMF, NeuMF, and ItemKNN-CB. Given that the relevance scores distribution is highly dense, even a small improvement in Consistency may completely overturn the list of recommended courses. We conjecture that the range of $\lambda$ to be investigated for a given algorithm, largely depends on the density of the relevance scores, leading to the following observation:

**Observation 9.** The density of the relevance score distribution returned by an algorithm influences the trade-off between accuracy and consistency, after applying our approach. The higher the density, the higher the drop in accuracy.

**Qualitative Inspection.** The proposed principles and the corresponding consistency and equality metric directly measure properties of the recommender lists, and the experiments demonstrated that our approach leads to more consistent and equal learning opportunities. However, it may also be interesting to inspect some recommended lists resulting from a traditional recommendation algorithm and how they change after our approach. This comparison would close the circle with respect to the problem that motivated this study and helps the reader to assess the end-to-end impact of the proposed approach.

Table 2 shows how the list of recommended courses changes after applying our procedure. First, regarding affordability, it can be observed that the re-ranked list offers a broader range of opportunities in terms of fees, even among courses from the same category. This aspect may enable a learner to receive suggestions that can better fit with his/her current financial resources. Then, more diverse opportunities were proposed at both instructional level and asset types, which is linked with the targets pursued by the platform owners. Except for courses with a large class suggested in the first position, our approach leads to recommending courses with smaller classes that can better manageable. However, this comes at the price of a slight loss in the validity
Table 2: Impact on Recommendation. Sample top-10 recommendations provided to a learner by the traditional recommender system based on ItemKNN-CB (top) and the top-10 recommendations resulting from our approach.

and category diversity. This happened because the learner mostly interacted with “development” and “it-and-software” courses in the past, so our approach promoted courses more familiar for the learner. It should be noted that a scenario where platform owners would be interested in improving also category diversity requires to include it into the set of considered principles.

While the proposed approach confirmed its feasibility for improving multiple principles into a recommended list and more equal learning opportunities among learners, it should be noted that it is ultimately up to the stakeholders to select the principles and the trade-offs most suitable for their context.

5.3 Discussion

With increasingly digital educational systems, online course platforms represent an essential tool for learners who wish to identify the most suitable learning material, meeting their expectations of educational value. Due to the highly subjective and contextual nature of this process, platform owners need to consider multiple perspectives. Indeed, besides providing a wide range of course filtering options, an increasingly high number of principles for further processing such options is needed, in order to identify the most suitable ones for a learner. In this view, an in-depth understanding of recommendations
in online course platforms is functional to reduce the overload on both the learners and the platform owners’ sides, improving consistency and equality.

Our analysis in Section 4 indicates that optimizing recommendation algorithms only for learners’ interests may result in undermining other essential properties conveyed by the learning opportunities proposed to them. Ranges of educational recommendation algorithms, such as Bridges et al. (2018); Rieckmann (2018); Bhumichitr et al. (2017), can thus capitalize on our definitions, metrics, and procedures as a complementary mean for assessing the consistency of the recommendations, from a broader perspective. Furthermore, the re-ranking procedure proposed and assessed in Section 5 has been proved to improve equality across learners, counteracting potential pitfalls of data-driven educational recommender systems. This aspect becomes critical in large-scale contexts, especially while reaching out to all the stakeholders who are currently reluctant to the use of data-driven procedures (see Herold (2017)).

Furthermore, to complement to this kind of investigation, our work can be broadly envisioned as a way to embed views and needs of multiple educational stakeholders into the resulting recommended lists (Abdollahpouri et al., 2020). Such critical appraisal, operationalized in our framework by the interests of learners and the principles of platform owners, is a timely key to enhance our understanding of artificial intelligence more broadly, as emerged from recent works of Burke and Abdollahpouri (2016); Zheng (2019); Zheng et al. (2019). Such a multi-sided view would engage researchers with broader discussions on concerns regarding bias, fairness, and equality across stakeholders, which are likely to emerge, especially in large-scale digitalized educational platforms.

5.4 Limitations

Since our observations varied over algorithms and principles, we identified the main implications and limitations of our study.

- **Limitations of data.** While our results highlight the need to consider equality of learning opportunities when evaluating recommenders, the learners of COCO may not be representative of general learners in the recommender system. Unfortunately, data with sufficient attributes to look for sophisticated principles is difficult to find. As we pointed out in Section 4.1, other datasets include only few metadata of learners and courses.

- **Limitations of principles.** While our principles shed light on important aspects underlying the ranked courses, they may not be representative of the principles targeted by a specific platform or institution. Furthermore, in more traditional scenarios, the inspection of such principles is usually based on textual guidelines, and the translation into numerical indicators (when performed) is subjected to the specificity of the platform or institution. Our measures are just representative examples of how traditional text-based principles could be operationalized and enriched based on the peculiarity of the online context (e.g., manageability). However, our framework can be easily adapted to any (number of) principles, based on the pursued goals.
– **Limitations of algorithms.** Our study involves eight representatives recommendation algorithms from four families, but other types of algorithms may benefit from our procedure. However, to better focus on the evaluation of our contribution and due to the limitations of the underlying data, we constrained our study to algorithms that are key building blocks in several recommender systems.

– **Limitations of evaluation protocol.** Our results cannot prove that the differences in measured metrics translate to better educational outcomes and learners’ acceptance. Further studies with online evaluation are needed to complement these results. However, we conjecture that our results can provide an essential contribution to reach this goal, and offline protocols can be useful to select algorithms prior to deployment.

– **Limitations of metrics.** Among the myriad of metrics that can be used for evaluating a recommender system, we focus on consistency and equality to better assess our contribution. We also measured NDCG because it maps well to recommendation utility. However, consistency and equality do not consider the position of the course in a list, which can be important in particular legally-regulated recommendation contexts, as an example. Our study focused on a more general perspective to reach a broader audience.

6 Conclusions

In this paper, we introduced a new metric of learning opportunity equality among learners in the context of personalized recommendations. Then, we proposed a re-ranking procedure able to maximize it, according to the principles that platform owners desire to ensure for all learners. We envisioned a list of sample principles, and we assessed the impact of supporting learners with our approach on accuracy and beyond-accuracy metrics.

Based on the results, we can conclude that:

1. Recommendation algorithms tend to produce ranked lists with disparate equality of learning opportunities across learners, especially when the algorithm uses only user-item interactions as training data.
2. According to our principle definitions, equality of quality, validity, and manageability is guaranteed by different recommenders. Familiarity, affordability, learnability, and variety exhibit strong deviations over algorithms.
3. Optimizing recommendations for high consistency with respect to a given set of principles lead to higher equality of learning opportunities. This is stronger when the same weights are given to principles for all learners.
4. Controlling learning opportunity results in higher familiarity, variety, and affordability while maintaining stable values for the other principles. However, quality may experience small losses after applying our procedure.
5. The impact of our approach on accuracy and consistency depends on the density of the relevance score distribution of the original algorithm. The higher the density, the higher the drop in accuracy.
The framework depicted in this study can fit with a variety of applications both within the educational context and in other contexts. There is room for considering how additional algorithms respond to evaluation and what internal mechanics contribute to more uniform consistency and equality. How recommender consistency and equality compare across new and platform-specific principles may be particularly interesting. Furthermore, as real-world applications should consider whether their recommender systems provide consistent and equal learning opportunities across learners, we believe that there will be an increasing amount of research related to our study from the industry.

With this study, we highlighted that our framework is quite broad and incorporates elements of societal and ethical importance. It may be inevitable that, as recommender systems move further into education, it becomes more and more necessary that they embed strategies like the one we presented.

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