Personalization in Human-AI Teams:
Improving the Compatibility-Accuracy Tradeoff

Jonathan Martinez  Kobi Gal  Ece Kamar
Ben-Gurion University, Israel  Microsoft Research, USA
Levi H. S. Lelis
University of Alberta, Canada

Abstract
AI systems that model and interact with users can update their models over time to reflect new information and changes in the environment. Although these updates can improve the performance of the AI system, they may actually hurt the performance for individual users. Prior work has studied the trade-off between improving the system accuracy following an update and the compatibility of the update with prior user experience. The more the model is forced to be compatible with prior updates, the higher loss in accuracy it will incur. In this paper, we show that in some cases it is possible to improve this compatibility-accuracy trade-off relative to a specific user by employing new error functions for the AI updates that personalize the weight updates to be compatible with the user's history of interaction with the system and present experimental results indicating that this approach provides major improvements to certain users.

1 INTRODUCTION
Advancements in AI and ML have led to advice provisioning systems that derive insights and make predictions from large amounts of data. For example, expert diagnostic systems in healthcare predict patients’ health condition by analyzing lifestyle, physical health records and social activities, and make suggestions to doctors about possible treatments [1]. As the user interacts with the system, two processes occur. First, the user develops a mental model of the system’s capabilities based on the quality of the recommendations. Second, the system collects more data and is able to update its prediction models. While updating the system model can improve accuracy, it can also change the way the system makes predictions in a way that does not agree with the user’s expectations or mental model of the system. Thus while the update improves the overall system performance, it may exhibit a poor compatibility with the user’s expectations [2], possibly causing the user to lose trust in the system and ignore its recommendations.

As an example, imagine a doctor that is being assisted by AI that predicts whether skin moles are cancerous or not. Suppose that the system’s average accuracy is currently 70% overall, and that the doctor’s speciality is face skin moles. Next, the system receives an update which increases its average accuracy to 90% overall but reduces it to 60% for face skin moles. As a consequence of this poorly compatible update the doctor may notice the drop in accuracy regarding this specific region. As a result, the doctor may mistrust the system and start ignoring the system’s predictions, missing out on the benefits of being assisted by an intelligent system. Or worse still, the doctor may not notice this drop in accuracy on prediction in skin moles and consequently continue trusting the system’s predictions that happen to be less accurate after the update.

Bansal et. al. [2], suggested a method for adjusting the compatibility of updates to AI systems where the loss function is modified to incur an additional penalty for new mistakes, i.e., mistakes that the system’s post-update version makes that the pre-update version didn’t make. In the same research they show that a trade-off exists between the compatibility of the update and the accuracy of the updated version of the system: The more an update is forced to be compatible, the bigger loss in accuracy it will incur. The methods explored in this previous work were designed to lower the overall amount of new errors, meaning that they give the same importance to all instances in the data-set and disregard any specific user’s history of interaction.

Our hypothesis is that improvements in the compatibility/accuracy trade-off can be achieved by personalizing the update to specific users or a grouping of instances by some categorical column, since giving an additional penalty only for new mistakes made in instances that they are actually interested in (instead of all the instances in the training set) can potentially weaken the constraint put on the update and allow it to achieve a better compatibility-accuracy trade-off, i.e., achieve a higher degree of compatibility without sacrificing more accuracy compared to previous methods [2]. We propose various methods for personalizing the system update to the needs of a specific user and present the results of an off-line experiment that tests our hypothesis performed on various data-sets where, even though the results vary from user to user, an improvement in the average trade-offs can be clearly observed in certain classification tasks.
2 ADJUSTING COMPATIBILITY

In [2] a mathematical definition for the compatibility score of an update was introduced.

Definition 2.1. The compatibility score of an update:

\[ C(h_1, h_2) = \frac{\sum_x \mathbb{1}(h_1(x) = h^*(x)) \cdot \mathbb{1}(h_2(x) = h^*(x))}{\sum_x \mathbb{1}(h_1(x) = h^*(x))} \tag{1} \]

Where \( h_1 \) is the system’s pre-update hypothesis or prediction model, \( h_2 \) is the post-update model, \( h_i(x) \) is the label that model \( i \) predicts for instance \( x \), \( h^*(x) \) is the correct model (therefore \( h^*(x) \) is the correct label for \( x \)) and \( \mathbb{1}: \text{boolean} \mapsto \{0, 1\} \) is an indicator function that returns 1 if the expression received as the argument is true and returns 0 otherwise. The compatibility score of an update approaches 1 as the post-update model \( h_2 \) makes less new mistakes (mistakes that the pre-update model \( h_1 \) didn’t make) and approaches 0 as the opposite occurs.

In order to increase the compatibility score of an update, the notion of the dissonance of an instance \( x \) given an update to the system was introduced by the same research [2].

Definition 2.2. The dissonance of an instance given an update:

\[ D(x, h_1, h_2) = \mathbb{1}(h_1(x) = h^*(x)) \cdot L(x, h_2) \tag{2} \]

Where \( L(x, h_i) \) is a regular loss function that penalizes a model \( h_i \) for wrongly predicting the target label of an instance \( x \) (e.g. cross-entropy loss). Dissonance is a loss function that measures the degree to which the post-update model disagrees with the pre-update model and is designed to penalize a low compatibility score: It penalizes a mistaken prediction for \( x \) made by the post-update model \( h_2 \) only when the pre-update model \( h_1 \) made the correct prediction for \( x \). These are exactly the kind of mistakes that reduce the compatibility score of the update. Therefore, by training the model to minimize the loss incurred by the dissonance penalties, these kinds of mistakes are also reduced, increasing the compatibility score.

The loss function proposed by [2] to be used in the re-training (update) of an AI system includes the regular loss\(^1\) and the loss incurred by the dissonance function, weighted by the dissonance weight \( \lambda \in [0, 1] \):

\[ L_u(x, h_1, h_2, \lambda) = (1 - \lambda) \cdot L(x, h_2) + \lambda \cdot D(x, h_1, h_2) \tag{3} \]

The trade-off between compatibility and accuracy of the post-update model \( h_2 \) can be adjusted by modifying the value of the dissonance weight \( \lambda \). Increasing the value of \( \lambda \) will likely increase the compatibility score of \( h_2 \) while simultaneously decreasing its accuracy as it’s forced to make predictions similar to those the pre-update model \( h_1 \) makes. The purpose of this loss function is to decrease the overall number of new mistakes that \( h_2 \) makes.

Returning to the example with the doctor that deals mainly with face skin moles, once both the regular loss and the loss from dissonance are taken into consideration when updating the system (using Equation 3) less new mistakes will be introduced by the update while unfortunately sacrificing a certain amount of improvement in the overall accuracy. In our example, not accounting for dissonance will lead to a post-update average accuracy of 90% overall and of 60% for face skin moles, while accounting for it will lead to a post-update average accuracy of 80% overall and of 70% in face skin moles.

3 PERSONALIZED UPDATES

We suggest that the constraint put on the update by the the loss function from Equation 3 is more limiting than it should be and can be improved by considering the dissonance relative only to specific users since new mistakes can be forgiven when they occur in areas that the user does not interact much with. We hypothesize that weakening the constraint in this manner will improve the update’s compatibility-accuracy trade-off, i.e., make it reach the same compatibility score while sacrificing less accuracy.

In our example, suppose that instead of considering the dissonance obtained from all interaction instances in the data-set we consider only the dissonance from the instances most similar to the ones in the doctor’s history of interaction, effectively tailoring the update to obtain a model personalized to the doctor’s needs that achieves an average accuracy of 70% overall (in all regions, including those the doctor does and doesn’t interact with) but of 90% in the regions that the doctor interacts with the most.

Let \( u \) be a user or a grouping of instances by some categorical column\(^2\), \( H_u \) the history of interaction between \( u \) and the system and \( \text{train}(h_2) \) the large and general train set (that contains instances from multiple \( H_u \)) employed for the update. We now present various update methods for achieving a post-update model that is as accurate as possible by using \( \text{train}(h_2) \) and compatible with \( u \) by using \( H_u \).

3.1 Parametric approach

The first model we propose is parametric, in the sense that it computes the average value \( \mu_i \) of each feature \( i \) over all the instances \( x \in H_u \) where \( x = (x_1, \ldots, x_k) \) \((k \) is the number of features in the data-set) and uses the vector \( \mu = (\mu_1, \ldots, \mu_k) \) to approximate the likelihood \( P(x \mid H_u) \in [0, 1] \) that some instance \( x \) belongs to \( H_u \) as a Gaussian function:

\[ P(x \mid H_u) = \frac{1}{\sqrt{2\pi}\sigma} \cdot e^{-\left(\frac{|x - \mu|}{2\sigma}\right)^2} \tag{4} \]

Where \( \sigma \) is a parameter that can be adjusted to simulate different standard deviations\(^3\). Then, \( P(x \mid H_u) \) is

\(^1\)We added the \((1 - \lambda)\) that multiplies the regular loss as a normalization term.

\(^2\)A group of users, in a sense.

\(^3\)Using the actual deviations proved to be computationally costly and didn’t add significant accuracy.
employed by the loss function for incurring a bigger dissonance penalty for instances \( x \) that have a high likelihood of belonging to \( H_u \), or in other words, that have a larger likelihood of taking part in \( u \)'s future interactions with the system:

\[
L_p(x, h_1, h_2, H_u, \lambda) = (1 - \lambda) \cdot L(x, h_2) + \lambda \cdot D(x, h_1, h_2) \cdot P(x \mid H_u)
\]  
(5)

This approach makes the assumption that all the instances \( x \in H_u \) form a single cluster, since only the average of each feature is used for the likelihood computation. This may often not be the case, making the improvements in the compatibility/accuracy trade-off delivered by this approach limited. We chose to present this approach because it is intuitive and illustrates relatively well our approach to update personalization in general.

### 3.2 Non-parametric approach

The following update personalization models are non-parametric in the sense that they use the instances in \( H_u \) directly instead of computing general parameters (average and standard deviation) that describe the feature distribution in \( H_u \). Unlike in the parametric approach, this approach works well also when the instances \( x \in H_u \) form multiple clusters.

We begin by introducing a baseline model that follows the simplest approach to update personalization: Training a prediction model using only the user’s history as its train set. This model ignores the notion of dissonance, meaning that the predictions of the pre-update model aren’t taken into consideration. It employs the following loss function:

\[
L_b(h_2, H_u, \lambda) = (1 - \lambda) \cdot \sum_{x \in \text{train}(h_2)} L(x, h_2) + \lambda \cdot \sum_{x \in H_u} L(x', h_2)
\]  
(6)

Where the parameter \( \lambda \) is increased to gradually shift the obtained predictions from a model that trains using solely the general train set \( \text{train}(h_2) \) to one that does so with only \( H_u \) in order to plot this progression. If \( H_u \) is more useful than the general train set \( \text{train}(h_2) \) for predicting \( u \)'s future interactions with the system, a good model trained using this baseline loss function is expected to increase in accuracy as \( \lambda \) is increased, while an increase in the update’s compatibility is not guaranteed. This baseline is useful since the following personalization models are expected to provide improvements on average over the non-personalized approach (Equation 3) mainly when \( H_u \) is more useful than the general train set \( \text{train}(h_2) \) for predicting \( u \)'s future interactions.

The next model follows a more sophisticated approach to personalization by considering the dissonance from instances in \( H_u \) in an attempt to achieve a post-update model that is more compatible with the pre-update one regarding instances similar to those in \( H_u \). It employs the following loss function:

\[
L_0(h_1, h_2, H_u, \lambda) = (1 - \lambda) \cdot \sum_{x \in \text{train}(h_2)} L(x, h_2) + \lambda \cdot \sum_{x \in H_u} D(x', h_1, h_2)
\]  
(7)

The idea behind this model is to apply the smallest limitation possible to the update by giving the additional penalty from dissonance only for instances in \( H_u \), rather than for all the instances in \( \text{train}(h_2) \) as in previous methods [2] (Equation 3), such that \( u \) experiences post-update interactions that are compatible with the pre-update ones, i.e., \( u \) observes as few new mistakes as possible. A potential downside to this model is that it may perform poorly when dealing with a \( H_u \) that is too small to be helpful for predicting \( u \)'s future interactions.

The last non-parametric personalization model combines the non-personalized loss function \( L_b \) (Equation 3) with the dissonance loss obtained from \( H_u \) in the following loss function:

\[
L_1(h_1, h_2, H_u, \lambda, \lambda_c) = \sum_{x \in \text{train}(h_2)} L_c(x, h_1, h_2, \lambda_c) + \lambda \cdot \sum_{x \in H_u} D(x', h_1, h_2)
\]  
(8)

Here, as \( \lambda \) is increased (we experimented only with \( \lambda = \lambda_c \)), two different penalties from dissonance are received: One from the general train set \( \text{train}(h_2) \) and the other one from \( H_u \). This model may perform better than the previous one that employs \( L_0 \) since the small dissonance obtained from a small \( H_u \) can be compensated by the dissonance obtained from the large and more general set of instances \( \text{train}(h_2) \).

### 3.3 Hybrid approach

This model is very different from the previous ones because it doesn’t employ a customized loss function at all, meaning that it doesn’t make use of the dissonance loss (Equation 2) proposed in previous work [2]. Rather, it makes use of the instances in \( H_u \) to learn whether to use the pre-update version \((h_1)\) or the post-update one \((h_2)\) for predicting the label of any instance \( x \). This approach resembles the methods described in [3, 4]. To this end, an additional neural network \( h_{\text{ver}} \) is trained using \( H_u \) as its train set where the target label \( h_{\text{ver}}^*(x) \) of every \( x \in H_u \) for it to predict is set as follows (the data-set’s target label \( h^*(x) \) is ignored by \( h_{\text{ver}} \)):

\[
h_{\text{ver}}^*(x) = \begin{cases} 0 & h^*(x) = h_1(x) \neq h_2(x) \\ 1 & \text{otherwise} \end{cases}
\]  
(9)

Where, as a reminder, \( h^*(x) \) is the correct label of \( x \) (the dataset’s target label, not the label \( h_{\text{ver}}^*(x) \) that is solely used for \( h_{\text{ver}} \)’s training) and \( h_1 \) and \( h_2 \) are the system’s pre-update and post-update versions respectively. In other
words, \( h_{ver}(x) = 0 \) only when \( h(x) \) is a new error (an error that \( h_1 \) didn’t make) and \( h_{ver}(x) = 1 \) otherwise. Much like in dissonance (Equation 2), this stems from the fact that the only additional penalty necessary for increasing the compatibility of an update is for new errors while errors of any other kind can be forgiven. After \( h_{ver} \) is finished training, we get that \( h_{ver}(x) \in [0, 1] \) where a value closer to 0 means a bigger likelihood that \( h^*(x) = h_1(x) \neq h_2(x) \) so \( h_{ver}(x) \) should be equal to \( h_1(x) \) to avoid introducing a new error with the update. Finally, a cutoff value \( \lambda \in [0, 1] \) that is analogous to the dissonance weight is manually selected:

\[
h_{hyb}(x, \lambda) = \begin{cases} 
    h_1(x) & h_{ver}(x) < \lambda \\
    h_2(x) & h_{ver}(x) \geq \lambda
\end{cases}
\]

(10)

Where \( h_{hyb}(x, \lambda) \) is the label that the hybrid model predicts for an instance \( x \). \( \lambda \) serves as a dissonance weight since increasing its value increases the amount of labels that \( h_1 \) predicted to be taken. This approach is much more efficient than the previously mentioned approaches when generating a compatibility-accuracy trade-off curve because, instead of having to train a prediction model for each value of \( \lambda \), the output of \( h_{ver} \) can be used for any value of \( \lambda \). A downside of this approach is that the final weights of both \( h_1, h_2 \) and of any additional system versions to be trained have to be held simultaneously in memory in order to perform predictions.

4 EXPERIMENTS

The outline of the experiments we performed for validating the performance of the proposed personalization methods is the following (see Figure 1):

1. Split each history \( H_u \) into two disjoint sets\(^4\), a train set \( \text{train}_u \) and a test set \( \text{test}_u \). In our experiments we balanced both sets to contain equal amounts of each target class and \( |\text{train}_u| = 0.8|H_u| \).

2. Define \( \text{train}(h_2) = \bigcup_u \text{train}_u \) and select a small subset from it \( \text{train}(h_1) \subset \text{train}(h_2) \) to be used as \( h_1 \)'s train set (the pre-update model). In most experiments \( |\text{train}(h_1)| = 200 \) and \( |\text{train}(h_2)| = 5000 \) to reproduce the conditions in the experiments of [2].

3. For each \( u \):
   3.1. Train the personalization models using \( \text{train}(h_2) \) as the general train set \( \text{train}_u \) as the set to personalize to, i.e., \( \text{test}_u \) is hidden from the models to be used as a test set analogous to \( u \)'s future interactions with the system.

   3.2. Test all the models on \( \text{test}_u \).

4. Repeat the process for a number of folds in order to increase statistical significance, where in each fold a different random sample \( \text{train}_u \) is selected from \( H_u \).

5. Compute the average and standard deviation of compatibility and accuracy over all \( u \) in each fold weighted by \( |H_u| \).

We conducted this experiment with various data-sets. In the cases where the data-set didn’t contain information about actual users, the personalization was performed relative to a grouping of instances according to some categorical column. The experiment’s framework was implemented using Tensorflow\(^5\), where the models were realized as mostly shallow neural nets consisting of only sigmoid layers since the classification task was easy in most cases. The personalization didn’t contribute in hard classification tasks, we assume because of the information in \( \text{train}_u \) being too hard to generalize for \( \text{test}_u \). The implementation can be accessed via the following link: https://github.com/jonmartz/CompatibleUpdates.

In all the following plots, each point in each model’s plot corresponds to an update made with a different value of \( \lambda \), where the horizontal axis corresponds to the compatibility score and the vertical axis to the accuracy. The dotted line indicates the pre-update model’s accuracy and the “no hist” plot corresponds to the non-personalized model that employs the loss function denoted in Equation 3 for training. We compare the performance of the models by the following metric, named AUTC to differentiate it from any regular definition of AUC (Area Under the Curve):

**Definition 4.1.** The Area Under the Trade-off Curve (AUTC) of a post-update model is the area between its compatibility-accuracy trade-off curve (the curved plots shown in the upcoming figures) and the horizontal line that represents the pre-update model’s accuracy (the black dashed line).

Note that AUTC can also be negative when the trade-off curve generated by a post-update model is even worse on average than the horizontal line that represents the pre-update model’s accuracy. Also, in many cases the maximum compatibility that can be reached by some models is higher than that of other models, which may be giving those models an unfair advantage. This can be solved by cutting off the AUTC measurement at the maximum compatibility achieved by the model with the the smallest maximum

\(^4\)We performed a random split rather than a chronological one, because the proposed methods are not designed to handle strong shifts in the feature distribution.

\(^5\)https://www.tensorflow.org
compatibility but this version of the metric disregards the fact that some models reach better compatibility scores than others, which is a desirable trait.

4.1 Individual users

![Figure 2: Average compatibility-accuracy trade-offs with one standard deviation when grouping by the categorical column “relationship” in the ASSISTment data-set.](image)

(a) Weighted average over all $u$ in the experiment

(b) $78970 |H_u| = 510$

(c) $78903 |H_u| = 226$

Figure 2: Average compatibility-accuracy trade-offs with one standard deviation when grouping by the categorical column “relationship” in the ASSISTment data-set.

| Sub-figure | Models |
|------------|--------|
|            | no history | $L_0$ | $L_1$ | hybrid |
| (a)        | 0.0214 | 0.0218 | 0.0263 | **0.0308** | +43.4% |
| (b)        | 0.0034 | 0.0125 | **0.0134** | 0.0057 | +291.2% |
| (c)        | 0.0172 | 0.0279 | 0.0293 | **0.0368** | +113.6% |

Table 1: AUTC (Definition 4.1) of plots in Figure 2

The data-set used for this section’s experiment was one of the ASSISTment data-sets\(^6\) which was used in previous work as well [5, 6, 7, 8], where the classification task selected was to predict whether a student answers a question correctly on the first try or not. This data-set contains information about real-world users, so the personalization was performed relative to them. We suspect that a key feature for the successful personalization in this task was the skill-set the student requires for answering each question, since the distribution of this feature can vary greatly between students depending on what kind of questions are present in each student’s history.

Figure 2 shows the trade-off curves averaged over all 23 users in the experiment (Figure 2a) and the best two trade-offs for individual users. As seen in Figure 2a, the hybrid model hovers at an accuracy of around 5% higher than that of the non-personalized model (labeled “no history”, that employs Equation 3) on average, a relatively good improvement considering that the largest $H_u$ measured 510 instances long while $|\text{train}(h_2)| \approx 5000$. As seen in Table 1, the hybrid model’s AUTC is 43% better than that of the non-personalized model on average, while $L_1$ achieved a significant improvement of 291% for the user in Figure 2b.

4.2 Grouping by a categorical column

![Figure 3: Average compatibility-accuracy trade-offs with one standard deviation when grouping by the categorical column “relationship” in the Adult data-set.](image)

(a) Weighted average over all $u$ in the experiment

(b) Not-in-family $|H_u| = 1712$

(c) Unmarried $|H_u| = 436$

Figure 3: Average compatibility-accuracy trade-offs with one standard deviation when grouping by the categorical column “relationship” in the Adult data-set.

The data-set used for this section’s experiment was the

---

\(^6\)https://sites.google.com/site/assistmentsdata/home/assistment-2009-2010-data
4.3 Discussion

Observations regarding the trade-off curves obtained in the experiments:

- We found the improvement obtained by the baseline (Equation 6), i.e., the difference in accuracy between the point that corresponds to $\lambda = 0$ (when $\text{train}(h_2)$ is the model’s sole train set) and the one that corresponds to some other $\lambda$ (when $\lambda = 1$, $H_u$ is the model’s sole train set), to have a Pearson correlation of around 0.5 ($p-value \ll 0.0001$) with the trade-off improvement obtained by the personalized model $L_0$ (Equation 7), i.e., the difference in accuracy between the points that correspond to the same $\lambda$ in $L_0$’s and the the non-personalized model trade-off curves. This means that the baseline gives a good indication of how much improvement to expect from personalizing the update using $L_0$ compared to not personalizing the update. The rest of the personalized models don’t seem correlated to the baseline in this manner.

- Sometimes the hybrid model performs much better than the non-personalized model (Figure 2c) and sometimes much worse (Figure 3c). No convincing explanation for this behavior has been found, besides that $h_{ves}$ sometimes has a hard time choosing the correct model version with certain users.

- When $|H_u|$ is very small, only the hybrid model seems to improve both the accuracy and compatibility of the update, while all other models even tend to decrease both metrics as $\lambda$ increases. We speculate that most personalization models fail in this scenario because $|\text{train}(u)|$ is too small for learning something meaningful that can be generalized to $\text{test}(u)$, and that the hybrid model’s success stems from its resemblance to model ensemble methods whose improvement capabilities are robustly backed-up [4]. However, if $|H_u|$ is small and large amounts of data are available for general updates ($\text{train}(h_2)$) then avoiding personalization is likely to produce better results.

- Some plots exhibit an upward trend in accuracy. We speculate that accuracy rises as the model adapts to the feature distribution present in $H_u$ and falls as too much compatibility is demanded. The upward trend sometimes exhibited by the non-personalized baseline may be related to model ensemble theory [4], where considering multiple models simultaneously can provide better results than considering only one of them. In this case, the accuracy begins with a certain value as only the post-update model is considered ($\lambda = 0$), rises as the pre-update model’s dissonance is brought into consideration ($\lambda > 0$) and finally descends as the post-update model starts to be disregarded ($\lambda$ too close to 1).

A downside of all the personalization methods proposed in this paper is that if there are significant changes in the way $u$ interacts with the system, i.e. $u$’s future interactions differ from the ones in $H_u$, we don’t expect them to perform better than the non-personalized baseline method (Equation 3) since the personalization component the employ works with the assumption that future interactions will resemble the current ones.

5 RELATED WORK

This paper is strongly related to recent work of Bansal et al. [2] that introduces the update compatibility score (Equation 1) and proposes a method for increasing this score the updated model trains using a customized loss function that gives an additional penalty for mistakes that the pre-update version of the model didn’t make. They showed that demanding the update to be more compatible generally decreases the accuracy of the updated model, generating a compatibility-accuracy trade-off. We expand this method by adding a personalization component, i.e., that tailors the update to be compatible with the way a specific user interacts with the system with the goal of generating better compatibility-accuracy trade-offs (achieving the same compatibility score while sacrificing less accuracy).

---

Table 2: AUTC (Definition 4.1) of plots in Figure 3

| Sub-figure | Models           |
|------------|------------------|
|            | no history | $L_0$   | $L_1$   | hybrid |
| (a)        | 0.0180    | 0.0184  | **0.0188** | 0.0143 |
|            | +0%       | +2.6%   | **+4.9%** | -2.0%  |
| (b)        | 0.0233    | 0.0265  | **0.0266** | 0.0200 |
|            | +0%       | +13.5%  | **+13.6%** | -14.0% |
| (c)        | 0.0199    | **0.0236** | 0.0235  | 0.0133 |
|            | +0%       | **+18.6%** | +18.0%  | -33.2% |

well-known Adult data-set where the classification task is to predict whether a person earns more than 50K a year or not. This data-set doesn’t contain information about real-world users, so the personalization was performed relative to instances grouped by the categorical column “relationship”. The trade-off plots obtained can be seen in Figure 3 and the AUTC measure if the plots compared in Table 2. The performance of the personalization models in this experiment is poorer than the one observed in Section 4.1’s experiment. $L_0$ and $L_1$ hover at an accuracy of around a steady 1% higher than that of the non-personalized model. $L_1$ achieved an improvement in AUTC of around 5% on average, while the best improvement in AUTC for an individual category (or “group of users”) was of 18.6%, achieved by $L_0$. In contrast, the hybrid model’s AUTC is 2% less than that of the non-personalized model in average.
The underlying idea behind the method proposed in [2] (and therefore behind the personalization models proposed here as well) is similar to several other works. One such example are model ensemble methods [9], AdaBoost in particular [4]: In both methods, an additional penalty is received for certain mistakes depending on a previously trained model, where the methods depicted in this work receive this additional penalty for mistakes in instances that the previous model got right and AdaBoost for the ones that the previous model got wrong. After the most recent model is finished training, the methods depicted in this paper (except the hybrid one) discard the previous model while AdaBoost keeps them both and then selects which one to use according to certain metrics (similarly to the hybrid method, see Section 3.3). It would be interesting to theoretically explore these similarities.

Also, the hybrid model proposed is related to research on methods for choosing the best expert [3], the difference being that in our method we simply train a neural net to predict which model to use (pre-update or post-update). Further implementation of the ideas in [3] could improve the hybrid model’s performance. Several other works relate to model personalization, but do not address personalization regarding updates to the model and do not relate to the notion dissonance. For example, regarding the ASSISTment dataset classification task mentioned in Section 4.1, work was performed on individualizing student models [5, 6] and on clustering the students [7, 8] with the purpose of improving the prediction accuracy (related to the idea of “groups of users” in Section 4.2).

Much work has been done in the field of human-AI interactions. Update compatibility is closely related to the 14th Guideline for Human-AI Interactions from Amershi et al.’s work [10] described as “Update and adapt cautiously: Limit disruptive changes when updating and adapting the AI system’s behaviors” i.e. making sure that the post-update version conforms to the user’s mental model of the system that developed during the user’s interaction with the system’s pre-update version. It is related also to the 5th step in an article from Google Design [11] that states the importance of making sure that the AI-system and the user’s model evolve in tandem. For many more related works regarding human-AI interaction and AI-advised human decision making please refer to the related work section in Bansal et al.’s paper [2].

6 CONCLUSION

Update compatibility is very likely to be important for the adequate functioning of human-AI teams [12, 2]. Previous work addressed the problem of making updates compatible by developing a loss function that delivers an increased penalty for new mistakes, i.e., mistakes the post-update version of the system makes that the pre-update one didn’t, and showed that a trade-off between the compatibility and accuracy of the update exists [2]. We propose various update personalization models (Section 3) with the intention to deliver improved compatibility-accuracy trade-offs for specific users and experimental results that partially indicate that update personalization by these methods out-performs a non-personalization approach: Although the personalization models may provide only marginal improvements in average, they provide substantial improvements for certain users. In certain cases the use of the personalization methods provides a poorer trade-off than the not-personalized approach, but the experimental results indicate this to be the case only for a minority of the users that the models were tested on.

In general, most of the personalization models work mainly when the user history’s length $|H_u|$ is above a certain threshold. We speculate this happens due to $H_u$ having a small likelihood of being representative of the user’s future interactions (not sharing the same feature distribution) when $|H_u|$ is below this threshold. However, even when $|H_u|$ is above this threshold, it’s not always the case that the personalization models provide better trade-offs. This means that even though $|H_u|$ is potentially large enough to be employed for accurately predicting the user’s future interactions, $H_u$ will sometimes not generalize well to them even when strong shifts in the feature distribution are absent. Estimating whether the personalization models will contribute or not given only a superficial analysis of the data-set and users’ feature distribution is hard, but the proposed baseline model (Equation 6) may be provide good indication for this (see Section 4.3).

The bottom line is that, according to the experimental results, personalizing the updates for certain users by using the proposed models should be preferred since these models do not provide a worse compatibility-accuracy trade-off than the non-personalization approach on average, and for certain users, they provide a much better one.

---

8 This is true mostly for the model that employs $L_1$ denoted in Equation 8
References

[1] Abhaya Kumar Sahoo, Chittaranjan Pradhan, Rabindra Kumar Barik, and Harishchandra Dubey. Deepreco: deep learning based health recommender system using collaborative filtering. *Computation*, 7(2):25, 2019.

[2] Gagan Bansal, Besmira Nushi, Ece Kamar, Daniel S Weld, Walter S Lasecki, and Eric Horvitz. Updates in human-ai teams: Understanding and addressing the performance/compatibility tradeoff. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 33, pages 2429–2437, 2019.

[3] Mark Herbster and Manfred K Warmuth. Tracking the best expert. *Machine learning*, 32(2):151–178, 1998.

[4] Yoav Freund, Robert E Schapire, et al. Experiments with a new boosting algorithm. In *icml*, volume 96, pages 148–156. Citeseer, 1996.

[5] Yutao Wang and Neil T Heffernan. The student skill model. In *International Conference on Intelligent Tutoring Systems*, pages 399–404. Springer, 2012.

[6] Zachary A Pardos and Neil T Heffernan. Modeling individualization in a bayesian networks implementation of knowledge tracing. In *International Conference on User Modeling, Adaptation, and Personalization*, pages 255–266. Springer, 2010.

[7] Shubhendu Trivedi, Zachary A Pardos, and Neil T Heffernan. Clustering students to generate an ensemble to improve standard test score predictions. In *International conference on artificial intelligence in education*, pages 377–384. Springer, 2011.

[8] Shubhendu Trivedi, Zachary Pardos, Gábor Sárközy, and Neil Heffernan. Spectral clustering in educational data mining. In *Educational Data Mining 2011*, 2010.

[9] David Opitz and Richard Maclin. Popular ensemble methods: An empirical study. *Journal of artificial intelligence research*, 11:169–198, 1999.

[10] Saleema Amershi, Dan Weld, Mihaela Vorvoreanu, Adam Fourney, Besmira Nushi, Penny Collisson, Jina Suh, Shamsi Iqbal, Paul N Bennett, Kori Inkpen, et al. Guidelines for human-ai interaction. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, pages 1–13, 2019.

[11] Holbrook Lovejoy. Human-centered machine learning: 7 steps to stay focused on the user when designing with ml. https://medium.com/google-design/human-centered-machine-learning-a770d10562cd, 2017. Accessed Feb 2020.

[12] Gagan Bansal, Besmira Nushi, Ece Kamar, Walter S Lasecki, Daniel S Weld, and Eric Horvitz. Beyond accuracy: The role of mental models in human-ai team performance. In *Proceedings of the AAAI Conference on Human Computation and Crowdsourcing*, volume 7, pages 2–11, 2019.