Formalizing Customization in Persuasive Technologies

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Abstract. Many authors have noted that customization increases the effectiveness of persuasive technologies. Also, many empirical demonstrations of successful customization efforts exist in the persuasive technology literature. However, a clear formal framework to describe and evaluate customization is lacking. This leads to the worrisome conclusion that statements like: "customization is beneficial" are often ill-defined given the empirical demonstration at hand. In this paper we forward a formalization of customization to prevent such problems. We derive a number of assumptions regarding the data-generating model that need to be met for customization to be fruitful, and we provide several examples of customization criteria. This paper serves as a discussion piece for the persuasive technology conference to evaluate the use and value of (mathematical) formalizations of customization.

Keywords: Persuasive technology · Customization · Personalization

1 Introduction

In many fields of the social sciences (e.g., marketing, psychology, health-care, education, etc.) scholars are examining the effects of customized treatments (see, e.g., 2; 4; 8; 19; 14; 10). This is known under a multitude of headings (personalization, customization, etc. etc. (15; 1; 24)), and many studies can be found ostensibly showing the positive effects of customization (e.g., 21). However, the interpretation of statements like "customization of advertisements is beneficial" (2) or "personalization of medical information is more persuasive than non-personalized information" (9) is often ambiguous. This paper introduces a formal mathematical notation to describe the effects of personalization. This formalization clearly *defines* customization attempts and serves to *derive assumptions* regarding the data generating model and the customization process that are of use in experimental evaluations of customized persuasive technologies.

This paper is organized as follows: First, we briefly review customization and personalization efforts in the persuasive technology field. This review does not aim to provide a complete overview of earlier attempts, but merely serves to highlight the importance of customization to our field. Second, we provide a formalized view on customization attempts and introduce the (mathematical)

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formalization we use throughout. In the third section of this paper we analyze the simplest customization attempt possible using the proposed formalization and derive a number of results regarding the data generating process involved in such a simple customization effort. Subsequently, we introduce a numerical example of the use of our framework to guide customization efforts for a more elaborate customization attempt. Finally, we discuss the limitations of our proposed framework and discuss possible future work.

2 Customization and Personalization in Persuasive Technologies

The persuasive technology field has witnessed a number of attempts to understand customization in persuasive technologies. Much of the work on on customization in persuasive technology is theoretically based on dual-process models—the Elaboration Likelihood Model (ELM) (7) in particular—to work out how new or established psychological traits moderate persuasion. This is warranted by experimental studies in psychology which demonstrate that trait differences in motivations, such as need for cognition (NfC, 7) exists, and that these differences influence the peripheral and central processing of persuasive messages. Traits like NfC predict (e.g.,) differences in the effects of argument strength on attitudes, the degree to which individuals rely on product characteristics versus source liking (e.g., 13), attitude strength resulting from processing a persuasive message (e.g., 12), and metacognition in persuasion (e.g., 26). Hence, using trait differences in information processing is a fruitful approach for the design of persuasive technologies.

Taking a more applied approach, persuasive technology researchers have also worked on applications of individual differences in the design of persuasive technologies directly. (18) developed a customized persuasive systems in which persuasive messages were customized based on questionnaire measures of user susceptibility, while (16) developed a customized persuasive system in which persuasive messages were tailored to users based on observed user responses. (6) developed a scale to measure persuadability of users for use in the customization process, and in a CHI 2014 workshop on *Personalizing Behavior Change Technologies* personalization was actively discussed.[1] Customization was examined in the context of persuasive technologies designed to improve sleeping behaviors (5), and authors have discussed general architectures for personalized persuasive systems (22) and persuasive system design. Also, under the heading of computer tailored health interventions, customization is heavily researched (see, e.g., 24; 20).

To summarize, customization, or personalization, is heavily researched within the persuasive technology community. However, a formal language to evaluate and compare customization efforts is lacking: while many studies conclude that

[1] http://personalizedchange.weebly.com/1/post/2014/03/the-crowd-and-persuasion-a-necessity-for-individualized-persuasive-technologies.html

customization is "beneficial" in one way or another, there is no consensus in the methods that demonstrate such statements. Hence, it is unclear what exactly customization means, what beneficial means, and compared to what type of non-customized system the statement holds. In the next sections we develop a formalization of customization that, we hope, reduces some of these problems.

3 A Formalization of Customization

In this section we introduce a mathematical formalization of customization (or personalization) efforts that are undertaken in the design of persuasive systems and in other fields. We then provide a simple application of the proposed formalization based on an existing customization study (17).

We start with a number of definitions useful to formalize the customization problem. Abstractly, each customization effort can be described according to the following terms:

Definition 1. *Treatments (or actions)* $\boldsymbol{a}_i$. *Here,* $\boldsymbol{a}_i$ *specifies the treatments (or messages, or feedback) that a user* i *receives.* $\boldsymbol{a}$ *is possibly a vector describing treatment values in a high dimensional treatment space.*

Definition 2. *User features* $\boldsymbol{x}_i$. *Here,* $\boldsymbol{x}_i$ *denotes all relevant characteristics of the user that are used in the customization process. Also* x *is possibly a vector.*[2]

Definition 3. *The (assumed) data generating function* $y_i = \mathcal{M}_g(\boldsymbol{a}_i, \boldsymbol{x}_i)$. *Here,* y_i *denotes some outcome measure of the customization attempt (e.g., compliance), and* $\mathcal{M}_g(\boldsymbol{a}_i, \boldsymbol{x}_i)$ *denotes the function that maps the treatments given to a user* i *to the observed outcome given the user's features.*

Definition 4. *A criterion* $\mathcal{C}$. *The criterion is a statement regarding the observed outcomes,* y_i, *of the customization process which formalizes the* goal *of the customization attempt. In the remainder of this paper we assume that we choose the criterion such that effective customization* maximizes *the criterion.*

The above formalization does not yet specify what is intended with statements like "customization is effective". We propose to formalize such a statement using what we coin a *customization function*:

Definition 5. *The customization function* $\boldsymbol{a}_i = \eta_c(\boldsymbol{a}_i^B, \boldsymbol{x}_i)$. *This function describes how a certain* baseline *treatment,* $\boldsymbol{a}_i^B$, *interacts with the user features,* $\boldsymbol{x}_i$, *to produce a* customized *treatment.*

Note that if the function $\eta()$ does *not* depend on $\boldsymbol{x}_i$, then the treatments are *not customized.* The simplest case of such a non-customized treatment is denoted by $\boldsymbol{a}_i = \eta_{nc}(\boldsymbol{a}_i^B) = 1\boldsymbol{a}_i^B$ which we denote by the *nc* (non-customized) subscript.

[2] Note that this definition of user features also combines the notion of segmentation – adapting treatments to subgroups of users – and personalization: only if a each user has a unique combination of feature values then the term "personalization" would be distinct from "segmentation".

To state that "customization is effective" is thus the same as stating that for *some* customization function $\eta_c(\boldsymbol{a}, \boldsymbol{x}) \neq \eta_{nc}(\boldsymbol{a})$, that is selected by the researcher, the value of the criterion $\mathcal{C}$ is higher than for *any possible choice* of $\eta_{nc}(a)$.

3.1 Operationalization of the Definitions

To explain how the above definitions describe a concrete customization attempt consider the customization attempt described by (17): in this paper the authors measure, using a survey, whether or not users are "persuadable" (e.g., receptive to persuasive messages). The authors identify both "high" and "low" persuadables. Subsequently, the authors send email messages that either contain persuasive arguments (such as *"Both physicians and general practitioners recommend at least 30 minutes of moderate activity, such as walking, during a day."*) or not to motivate users to participate in a health related activity. The authors (amongst other things) measure the interest in the health related activity using a click on the (email) message.

In this specific case the treatment a_i is a scalar denoting either the persuasive message or the non-persuasive message (e.g., $a \in \{0, 1\}$). The user features for each user i can also be represented by a scalar x_i denoting high or low persuadable users (thus, also $x \in \{0, 1\}$). The data generating model $\mathcal{M}_g$ describes the assumed relationship between the treatments and the user features. In (17) this model is not described explicitly, but a flexible model mapping the four (2×2) possible treatment-feature combinations to possible observed outcomes y is given by:

$$y_i = \mathcal{M}_g(a_i, x_i) = \beta_0 + \beta_1 a_i + \beta_2 x_i + \beta_3 a_i x_i + \epsilon_i \tag{1}$$

where ϵ_i denotes the noise in the measurements and $\theta = \{\beta_0, \ldots, \beta_3\}$ is a set of model coefficients that need to be estimated from empirical data.[3]

The customization function in this experiment is simple, and merely "flips" the treatment for the two possible user features:

$$a_i = \eta_c(a_i^B, x_i) = (1 - a_i^B)^{(1-x_i)}(a_i^B)^{x_i}$$

resulting in the fact that for a specific baseline treatment $a_i^B = 0$, the users with a feature value $x_i = 0$ receive the treatment 0, while users with a feature value $x = 1$ receive treatment 1 and vice versa.

Finally, the authors examine the percentage of users showing interest in each of the four treatment-feature combinations. This can be formalized into the criterion $\mathcal{C}_{perc} = 100 * \frac{\sum_{i=1}^{N} y_i}{N}$. Note however, that since N is a constant *given* the experiment, maximizing the criterion $\mathcal{C}_{perc}$ is equivalent to maximizing $\mathcal{C}_{sum} = \sum_{i=1}^{N} y_i$ which we regard quite a common criterion and denote "$\mathcal{C}_1$" from now on.

[3] Note that in this paper we do not discuss estimation methods and from now on for simplicity assuming that θ can be estimated without error.

4 Analysis of the 2 × 2 Customization Case

In this section we analyze the 2×2 customization study as presented in (17), and derive a number of general results regarding the data generating model $\mathcal{M}_g(a_i, x_i)$ which are general for the 2×2 setting and can thus be used to evaluate other customization attempts with the same formalization.

For "customization" to be effective — given the criterion $\mathcal{C}_1$, the customization function $\eta_c(a_i^B, x_i) = (1 - a_i^B)^{(1-x_i)}(a_i^B)^{x_i}$, and the non-customized assignment function $\eta_{nc}(\boldsymbol{a}_i^B, x_i) = 1\boldsymbol{a}_i^B$, and furthermore using the assumed data generating model specified in Equation 1 — the following must hold:

$$\underset{a^B}{\operatorname{argmax}} \sum_{i=1}^{N} \mathcal{M}_g(\eta_c(a_i^B, x_i), x_i)) > \underset{a^B}{\operatorname{argmax}} \sum_{i=1}^{N} \mathcal{M}_g(\eta_{nc}(a_i^B), x_i) \tag{2}$$

Using this mathematical formalization, we can derive the following facts in the 2×2 case:

Theorem 1. *Treating x as a random variable, personalization will not be effective (thus, the inequality presented in Equation 2 will not hold) if $V[x] = 0$ where $V[]$ denotes the variance of the random variable.*

The proof is omitted but intuitively obvious: if each user has the exact same features x, then $\eta_c()$ reduces to $\eta_{nc}()$ for all users i and hence $\mathcal{M}_g(\eta_c()) = \mathcal{M}_g(\eta_{nc}())$.

Theorem 2. *Given the data generating model defined in Equation 1 personalization can only be effective if $\beta_3 \neq 0$.*

Here again the proof is trivial: if there is no interaction between user features and treatments, then $\underset{a^b}{\operatorname{argmax}} \sum_{i=1}^{N} \mathcal{M}_g(\eta_c()) = \underset{a^b}{\operatorname{argmax}} \sum_{i=1}^{N} \mathcal{M}_g(\eta_{nc}())$ since, irrespective of the user features, there is a optimal choice for the treatment which will be optimal *for all users*.

Since Theorem 2 is intuitively obvious, one often finds empirical demonstrations of the benefits of personalization which show, using null-hypothesis significance tests, that $\beta_3 \neq 0$ by rejecting $H_0 : \beta_3 = 0$. However, even in the simple 2×2 case such a demonstration is, while necessary, not *sufficient* for the statement in Equation 2 to hold. This is true since:

Theorem 3. *With criterion $\mathcal{C}_1$ personalization is effective (in the sense specified in Equation 2 and with data generating model specified in Equation 1) if and only if*

$$\beta_1 + \beta_3 > 0 \text{ when } \beta_1 < 0 \text{ or } \qquad \beta_1 + \beta_3 < 0 \text{ when } \beta_1 > 0$$

or, in words, the interaction term is larger, and of opposite sign, then the main effect of the treatment.

The proof is simple and can be given by enumerating the different options of user features and treatment combinations for this simple setup. However, a more general method for deriving the proof is to differentiate $\sum_{i=1}^{N} \mathcal{M}_g()$ with respect to a for both η_{nc} and η_c, setting to zero to find its maximum, and comparing $\mathcal{C}_1$ evaluated at that point for both the cases of η. Note that in applied cases $\boldsymbol{x}$ will be *given* by the population distribution of the user features and is thus a *constant* when determining properties of $\mathcal{M}_g()$.

Using the data presented in Table 1 of (17) and focussing on the first dependent measure ("Interest") we obtain – using a logit link function – $\beta_1 = 1.0116$ and $\beta_3 = -1.1163$ and thus, if we take theses point estimates as *true* values of $\mathcal{M}_g()$, the authors have indeed shown that personalization was effective in their experiment (although not very convincingly).

5 Continuous Treatment Personalization

To demonstrate the versatility of the formalization of customization that we present here, we explore another case in which both the treatment a is continuous, and the feature x is continuous (but again both are one-dimensional). Here we focus on the use of the introduced formalization to determine a customization function $\eta()$.

The following scenario describes a case in which this setting realistically occurs: suppose we are designing a persuasive technology that aims to motivate knowledge workers to lead a healthy lifestyle (See, e.g., 11). The system could send messages with suggestions for walks of different lengths (in kilometers), and the system could measure, using GPS, the number of kilometers a user actually walks. The suggested number of kilometers by the systems possibly interacts with the age of the user. Thus we have:

– Actions $a_i \in \{0, \dots\}$, the suggested number of kilometers for the walk.
– User features $x_i \in \{0, 99\}$, the age of the user.
– Outcomes y_i: the number of kilometers that the user ends up walking after receiving the suggestion.

Let us further suppose that we have carried out a large randomized experiment testing different messages, for a large set of users, with diverse ages (and thus with variance in the features in the dataset), and that we have measured their respective responses. We (ostensibly) find that a model that fits the data well is the following:

$$y_i = \mathcal{M}_g(a_i, x_i) = -\frac{1}{4}\left(a_i - (15 - \frac{1}{4}x_i)\right)^2 + 10 + \epsilon_i \tag{3}$$

where ϵ is some random noise with $E[\epsilon] = 0$ which is plotted (discarding ϵ) for users of different ages, $x \in \{20, 30, 40, 50\}$, in Figure 1. Basically the model describes that for suggestions that are either too low or too high, users fail to comply with the suggestion. In between a "best" suggestion can be found leading to the largest observed outcome. However, older users are more likely to regard a suggestion as too high: thus, the same suggestion has a different effect for users of different ages (hence, there is an interaction between user features and assigned treatments).

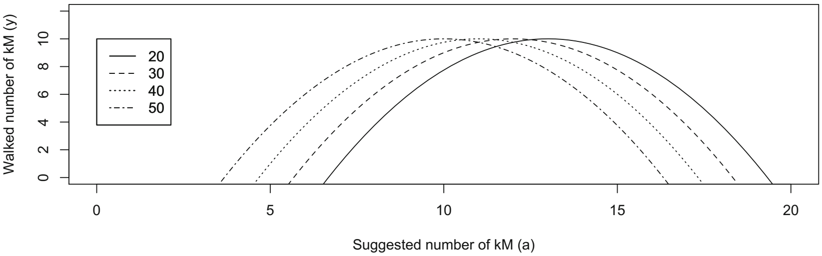

Fig. 1. Relationship between the suggested number of kilometers a, and the observed number of walked kilometers y, for users of different ages as described by the model specified in Equation 3.

5.1 Evaluating Customization for $\mathcal{C}_1$

Now that we have a formulation of the actions, features, and outcomes, and furthermore have specified the data generating model, we can use our formalization to find a customization function which maximizes an outcome criterion such as the sum of the outcomes over all users, $\mathcal{C}_1$.

Suppose we aim to treat a population of 1000 users, with ages distributed uniformly random between 20 and 50. We can then explore whether a specific customization function $\eta_c()$ "outperforms" a non-customized version of treatment selection (formalized by $\eta_{nc}(a_i^B, x_i) = 1a_i$). Figure 2 presents the value of $\mathcal{C}_1$ for a group of 1000 users as a function of a_i^B for the non-customized version (solid line), and various customization functions (dashed lines) given by:

$$\eta_c(a_i^B, x_i, \beta) = a_i^B - \left(\frac{1}{\beta} * (x_i - 20)\right) \tag{4}$$

where $\beta \in \{1, 5, 10, 15\}$. This customization function formalizes the idea that users with a high age (x value) should receive lower suggestions. As is clear from Figure 2, with the appropriate choice of β, customization can outperform non-customized messaging in this specif case.[4] The maximum value of $\mathcal{C}_1$ for the non customized version is (on average, dependent on the simulation run) about 9819 (averaged over 100 simulation runs), while for the customized version, with $\beta = 10$, a maximum value of 10000 can be obtained (regardless of the simulated ages).

5.2 Evaluating Customization for Alternative Criteria

In the previous section we examined the customization function defined in Equation 4 using criterion $\mathcal{C}_1$. However the proposed formalization of customization allows for the investigation of different types of objectives of customization at-

[4] And, obviously, given this particular choice of customization function.

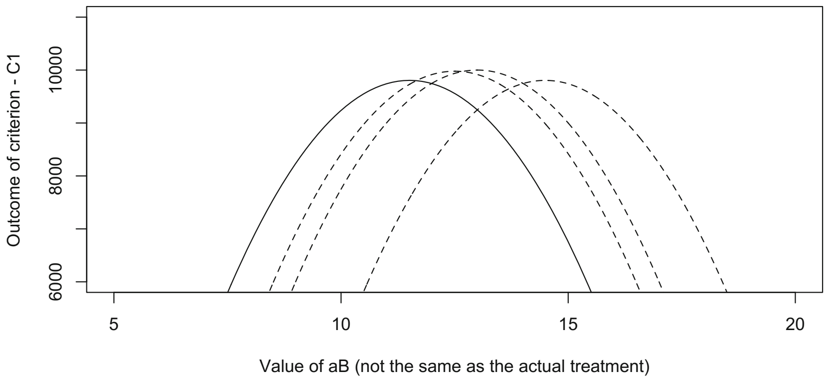

Fig. 2. Values of $\mathcal{C}_1$ as a function of a_i^B for different values of β in Equation 4. Note that several customization functions outperform the non-customized version (solid line), and that the highest value of $\mathcal{C}_1$ can be obtained using $\beta = 10$.

tempts. For example, we could also specify as a criterion:

$$\mathcal{C}_2 = -1 \times \sum_{i=1}^{N} (y_i - k)^2$$

where k is a constant denoting the optimal value of the outcome for individuals (which, in this case, is the same for all individuals). Setting $k = 10$ — and thus denoting that the *optimal* walk length is 10 kM, and both longer and shorter walks are infeasible — we can again numerically examine the criterion as a function of a^B. Figure 3 shows, for $\beta \in \{1, 5, 10, 15\}$ the possible outcomes. Here again, given the appropriate choice of β, customization clearly outperforms non-customized messaging. Note that in each case 2 distinct values for a^B maximize the criterion, hence two different baseline treatments would lead to the same outcome(s) in this specific setting.

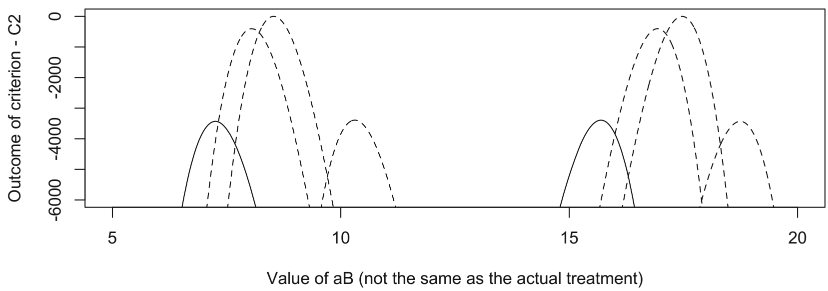

Fig. 3. Values of $\mathcal{C}_2$ as a function of a_i^B for different values of β in Equation 4. Note that several customization functions outperform the non-customized version (solid line), and that the highest value of $\mathcal{C}_1$ can again be obtained using $\beta = 10$. Also note that there are two possible maxima for each customization method.

6 Discussion

In this paper we presented a possible formalization of customization attempts consisting of a description of:

- Actions (or treatments) $\boldsymbol{a}$.
- Features of the user, $\boldsymbol{x}$.
- Observed outcomes y provided by the data generating function $\mathcal{M}_g(\boldsymbol{a}, \boldsymbol{x})$.
- The customization function $a_i = \eta_c(a_i^B, x_i)$.
- A criterion $\mathcal{C}$.

We have demonstrated that using this formalization seemingly distinct customization efforts can be formally described, and that the formalization can be of use to disambiguate statements regarding customization. Furthermore, the introduced formalism can be used to a) derive features of the assumed data-generating model $\mathcal{M}_g$, and b) determine optimal customization functions $\eta()$. However, we consider the current article merely a starting point: the value of methods to (mathematically) formalize customization attempts for the persuasive technology field remains to be seen. Notably, relationships between the currently proposed formalization, and those proposed in surrounding fields (see, e.g., 3; 25; 23) need further discussion. In the remainder of this discussion section we introduce a number of possible extensions to the formalization and some practical problems that can be foreseen.

6.1 Criteria

In this article we introduced two possible criteria to evaluate customization: $\mathcal{C}_1$ denoted the summed overall outcome y, while $\mathcal{C}_2$ denoted the squared distance from some objective for each user. The formalization presented in this paper however gives rise to alternative specifications of customization criteria. For example, one could consider:

$$\mathcal{C} = \sum \mathbb{1}\{y_i > k\}$$

as a personalization criterion where $\mathbb{1}$ denotes the indicator function and thus the criterion states to maximize the number of users that have at least outcome k. Contrary to $\mathcal{C}_1$ this customization function does not consider the absolute size of y_i, but rather only the passing of a certain threshold.

6.2 Estimation

In this paper we have not discussed the role of empirical data in the estimation of $\mathcal{M}_g$. In most practical situations $\mathcal{M}_g$ will be unknown and both model selection as well as parameter estimation need to be undertaken to find a suitable form. In practice the estimated coefficients (e.g., β's in Equation 3) will contain error that need to be considered when examining different customization functions.

6.3 Analytical Solutions

In this paper, and primarily in Section 5, we have presented a number of numerical (based on simulations) results of customization functions. However, there is a clear analytical procedure available once the customization function is selected: one merely plugs in the customization function into the data generating model, and evaluates its maximum (given the chosen criteria and possible population estimates of $\boldsymbol{x}$) by differentiating with respect to $\boldsymbol{a}^B$. In practice this might be cumbersome for a high dimensional set of features and possible treatments, however, theoretically this provides a clear method to evaluate different customization functions. This needs further demonstration.

6.4 Dynamic (over-time) Customization

The current paper introduced a formalization of customization in which fixed features x, and a single treatment a per user are considered. In practice, we observe more and more customization efforts which are dynamic over time (e.g., 16). In these cases the action $a_{(i,t+1)}$ selected for user i at timepjoint $t+1$ depends on $y_{(i,t)}$, the observed outcome at time t. We currently think that such attempts can easily be reconciled with our formalization by using $y_{(i,t)}$ as a feature when customizing for $y_{(i,t+1)}$. However, the applicability of our framework for dynamic customization attempts needs future work.

6.5 Conclusions

In this paper we forwarded an initial attempt to formalize customization efforts in persuasive technology. Based on this formalization we derived a number of assumptions of the (assumed) data-generating model that need to be met for customization to be fruitful, and we provided several examples of definitions of customization and their implications. This paper should serve as a discussion piece for the persuasive technology conference to evaluate the use and value of (mathematical) formalizations of the customization process for the design of persuasive systems.

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