PERSONALIZED EXPLANATION FOR MACHINE LEARNING

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Abstract

Explanation in machine learning and related fields such as artificial intelligence aims at making machine learning models and their decisions understandable to humans. Existing work suggests that personalizing explanations might help to improve understandability. In this work, we derive a conceptualization of personalized explanation by defining and structuring the problem based on prior work on machine learning explanation, personalization (in machine learning) and concepts and techniques from other domains such as privacy and knowledge elicitation. We perform a categorization of explainee information used in the process of personalization as well as describing means to collect this information. We also identify three key explanation properties that are amendable to personalization: complexity, decision information and presentation. We also enhance existing work on explanation by introducing additional desiderata and measures to quantify the quality of personalized explanations.

Keywords: Explainable Artificial Intelligence, Interpretable machine learning, Personalization, Customization, Interactive machine learning

1 Introduction

Techniques allowing to extract knowledge from data, such as machine learning and related fields such as artificial intelligence, have been growing rapidly in importance over the last years. For once, automatic decision-making utilizing techniques from these fields is more and more supporting or replacing human decision making in many areas such as computer vision, speech recognition and natural language processing (Goodfellow et al., 2016). This is partially grounded in the emergence and improvement of complex techniques such as deep learning, which has pushed the state-of-the-art for multiple problems in these areas (Goodfellow et al., 2016). Unfortunately, techniques such as deep learning are hard to understand for humans, earning them the title "black boxes". As a consequence, research is often driven by empirical evaluation compared performance metrics only without the necessary underpinning using theory or, even, a thorough qualitative understanding using case-based research. Furthermore, systems involving such techniques are often deemed non-trustworthy since they are susceptible to surprising errors, i.e. they can be fooled in ways humans cannot (Nguyen et al., 2015). These facts underpin the need for explanations enabling a deeper understanding. Another driver for increased interest in explanation has been legislation, i.e. the European parliament introduced the General Data Protection Regulation (GDPR) as of May 2018. It grants individuals the right for "meaningful explanations of the logic involved" for outcomes involving automated decision making.

To obtain meaningful and easy to understand explanations, the literature on machine learning has already expressed the need to focus on humans rather than just on technical aspects of machine learning (Adadi and Berrada, 2018; Doshi-Velez and Kim, 2017; Došilović et al., 2018; Ras et al., 2018). (Adadi and Berrada, 2018; Doshi-Velez and Kim, 2017; Došilović et al., 2018; Ras et al., 2018)It has also been emphasized that explanations should be personalized, meaning they should be tailored to individuals. The literature to this date, however, has almost exclusively adopted the idea of personalized explanation, when personalization was part of the task performed by the machine learning model to be explained. For example, in recommendation systems that utilizes information on individuals such as submitted product reviews to derive predictions the idea of personalized explanations has been expressed (Zhang et al., 2014).

Thus, the idea to first extract knowledge from the explainee and then utilize this information to improve explanations has been largely absent in the existing literature. This work attempts to close this gap by discussing both steps. We provide an overview of the current state of personalization in explanation of machine learning. We provide a framework covering desiderata of personalized explanations, dimensions that can be personalized, what and how information can be obtained from individuals and how this information can be utilized to customize explanations. Finally, we also discuss on how to evaluate personalized explanation methods. We do so by surveying and synthesizing existing literature on "explanation in machine learning", "personalization in machine learning" and from other domains.

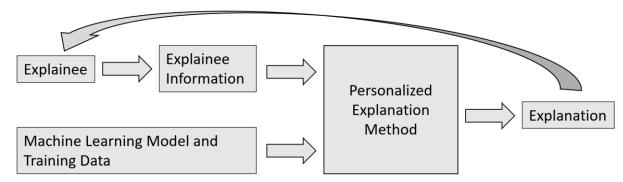


Figure 1. Overview of personalized explanation.

The structure of the paper is as follows: After providing background information (Section 3) and conceptualizing personalized explanation (Section 4), the paper largely follows the personalized

explanation process depicted in Figure 1. That is, we elaborate on explainee information and how to obtain it in Section 5, discuss personalized explanation methods and, finally, in Section 6 present means for evaluation.

2 Methodology

We conducted a narrative literature review (King and He, 2005) to investigate elementary factors and research outcomes related to personalized explanation in machine learning. To develop a framework, we utilized and adapted concepts, methods and ideas synthesized in systematic literature reviews conducted by fellow researchers from more established areas such as Explanation in Machine Learning, Personalization, Personalization in Machine Learning, Privacy and Knowledge Elicitation. Personalized Explanation in Machine Learning is an emerging field and, therefore, is more suitable to a qualitative approach such as narrative literature review than a more quantitative approach as found in descriptive reviews. We utilized established online databases from computer science as well as information systems such as IEEE Xplore, ProQuest (ABI/INForm), ScienceDirect (Elsevier), AIS electronic library and the ACM digital library. The development in computer science is very rapid with seemingly well-renowned authors publishing their articles first a year or more before on the "arxiv.org" platform before the conference proceedings are available. Furthermore, many articles are not published in journals at all. Thus, to give the reader the most up-to-date view on the topic we included conference articles as well as articles from "arxiv.org" after careful consideration.

3 Background

Personalization has been studied in multiple areas (Fan and Poole, 2006) such as e-commerce, computer science and cognitive sciences. Our work covers aspects from cognitive science during user modelling, i.e. we make "assumptions about users' goals, interests, preferences and knowledge based on an observation of behaviour [or other sources of information]", but also from computer science, when it comes to implementing user models into an IT system, i.e. we provide a platform that "supports individualized information inflow and outflow" (Fan and Poole, 2006).

Personalization in machine learning occurs in two ways: Machine learning has been used as a means for personalization, but it has also been subject to personalization itself. Examples of the former include machine learning algorithms for recommender systems (Cheng et al., 2016), web personalization and search (Chen and Chau, 2004). Personalization of machine learning includes works on interactive machine learning (Amershi et al., 2014), where one seeks to improve a machine-learning based system using an iterative design process involving potentially domain experts with little machine learning knowledge. To personalize, information such as preferences or task knowledge must be obtained. Special **elicitation** techniques might be required, in particular to extract tacit knowledge, which is hard to express verbally or in writing (Dieste and Juristo, 2011).

To "explain" means "to make known, to make plain or understandable" ("explain", n.d.). The related term "interpret" can be defined as "to explain or tell the meaning of" ("interpret", n.d.). Explanation seeks to answer questions such as: what, why, why not, what if, and how to (Lim et al., 2009). Gregor and Benbasat (1999) proposed the following explanation types: i) trace or line of reasoning, ii) justification or support, iii) control or strategic, and iv) terminological. The literature is not concise on using the terms. We prefer the term "explain", since we are less interested in the meaning of "machine learning" outcomes than in understanding those outcomes.

One of the earlier studies on **explanation in machine learning** was performed in (Huysmans et al., 2011). They investigated comprehensibility of decision trees, tables and rule-based methods. These are all deemed to be easily explainable, meaning that they can be easily understood by humans. For more complex techniques, a large amount of techniques have been developed in the last years that have been surveyed and placed into several taxonomies, e.g. (Ras et al., 2018) and (Guidotti et al., 2018).

4 Personalized explanation in machine learning

Personalized explanations in machine learning refers to deriving explanations of machine learning models and its decisions targeted to a specific individual or a group of individuals. To enhance the understanding of this definition, we refer to the high-level process depicted in Figure 1 and we outline desiderata of personalized explanation, introduce key concepts based on work on personalization and explanation. Then, we test the concepts for soundness and completeness by using them to characterize existing work on personalized explanation.

4.1 Desiderata of Personalized Explanation

Existing desiderata for explanation methods apply also to personalized explanation. Additional aspects such as privacy as well as effort for obtaining information from an explainee are also relevant and described in more detail:

- *Fidelity* the degree to which the explanation matches the input-output mapping of the model (Guidotti et al., 2018; Ras et al., 2018).
- *Generalizability* the range of model to which the explanation method can be applied (Ras et al., 2018).
- Explanatory Power the scope of questions that the explanation can answer (Ras et al., 2018).
- Interpretability the degree to which the explanation is human understandable (Guidotti et al., 2018). Fürnkranz et al. (2018) further distinguish an objective measure of the explanation's capability to aid the explainee in performing a task (comprehensibility) and a subjective measure of the explainee's acceptance of the explanation (plausibility).
- *Information collection effort* the effort that an individual needs to undertake to provide additional information needed for personalization. That is to say, it only refers to information that is collected with the sole purpose of obtaining personalized explanations. Thus, if information on the explainee is already available, e.g. as part of the training data for the machine learning model to be explained, the extraction effort is zero. The effort for the explainee might range from answering a few simple questions to repeatedly providing feedback on proposed explanations based on careful analysis.
- Privacy the degree to which information on the explainee is extracted, stored and used. Privacy is
 a key concern if information could become available to "adversaries", i.e. malicious parties. In such
 a case, privacy might be violated even if only anonymous data is compromised (Montjoye et al.,
 2015). Information on the explainee could be highly sensitive such as IQ allowing to determine a
 user's cognitive abilities or rather insensitive such as obtaining a user's preferred explanation
 method.

4.2 Conceptualization

The four concepts introduced in this chapter based on the implementation by Fan and Poole (2006) set the bases for later chapters. The concepts, two on machine learning explanation and the other two on personalization, are *explanator type*, *explanation properties*, *information extraction methods*, and *personalization mechanisms*.

The **explanator type** refers to the type of outcome of the explanation method. The explanator type influences how personalization may be done as types differ in their explanation strategies and representations. The following three types are adapted from (Molnar, 2018):

• Feature summary statistic and visualization (attribution) – pointing out how each feature affects the decision, e.g. features importance. Attribution can explain the relationships between a model's intermediate components, e.g. between two layers of a neural network. An attribution explanator points out how each contributor affects the attribution target

- *Data point* returning data points along with the machine learning outcome, e.g. class label, class probability, or cluster assignment, as explanations.
- *Model internals* returning the decision maker's internal representations of data points, e.g. structure of a decision tree, regression model, or feature visualization of a neural network.

Explanation properties are characteristics of an explanation that can be adjusted, i.e. used for personalization. We identified three explanation properties:

- *Complexity* refers to both the size of an explanation, e.g. rule length or decision tree depth, and relationships between features presented in an explanation, e.g. correlation (Paulheim, 2012) or conjunction (Fürnkranz et al., 2018).
- Prioritization of decision information refers to selection of features and feature relationships to present in an explanation. It is applicable on the feature space and input space. Prioritizing on the feature space means to construct an explanation by using a subset features or feature relationships. Selection in the input space refers to the subset of examples used to generate explanations. For example, let us assume there exists a novel disease diagnosis method with thousands of exemplary diagnoses of patients. To explain the diagnosis of a specific patient case to a pediatrician, a personalized explanation relying on choosing data points might rather choose patient cases of children than adults.
- *Presentation* refers to an explanation's presentation form, e.g. the choice between numbers and colors to depict intensity or the choice between natural language or logical expression to present decision rules.

Information collection indicates how information from the user, in our case the explainee, is obtained. Information can refer to knowledge, e.g. how a user solves the task, or to user preferences, e.g. preferred colors in displays. Implicit information collection refers to information which is obtained regardless of whether explanations are needed or not. This means, the information is part of the training data of the machine learning model, for example in recommender systems (Zhang and Chen, 2018). In contrast, explicit information collection, information is acquired using a process that might be separate from training data collection.

Personalization granularity focuses on "to whom to personalize", i.e. a category of individuals or a specific individual. Findings on social identity indicate (Fan and Poole, 2006) that people might behave more according to values and concerns associated with a social group in certain situations. Categorization might be a crude form of personalization, e.g. we might simply categorize users into experts or non-experts, rather than assessing different dimensions related to expertise and customizing along each dimension. However, given sufficiently many categorical attributes on an individual, such as age, gender, origin etc. might also lead to personalization to a specific individual.

Personalization automation focuses on "who does the personalization" (Fan and Poole, 2006), i.e. a manual personalization done by the explainee or an automatic one by the system providing explanations. Manual personalization corresponds to an explainee actively setting the explanation parameters, e.g. choosing the number of features to visualize.

4.3 Categorization of existing work

We assess existing work with respect to the concepts in Section 4.2. A summary is shown in Table 1. Researches in our literature review include works on: explanation methods and factors that may affect interpretability. Researches of the former are relevant as they give insights on the variety of ways explanations can be constructed. On the other hand, researches of the latter reveal factors for customization. These two aspects are furthered discussed in the next subsections. First, we describe key points of the literature summary in Table 1.

Two operationalisations are observed for complexity, namely size and interaction between features (Fürnkranz et al., 2018; Narayanan et al., 2018). The former refers to measures such as rule length, tree

depth, or linear model sparsity, while the latter refers to interactions such as disjunctions or conjunctions. Adjustments on prioritized features are mainly done on explanations for recommender systems, except for (Ross et al., 2017). As for adjustments on presentation, prior work compared explanation presentations such as numeric and Boolean feature values (Paulheim, 2012), textual and graphical (Chen et al., 2018; Quijano-Sanchez et al., 2017), and word tags and natural language texts (Chang et al., 2016). In terms of explanator types, the majority of the methods use model internals as explanations which is aligned with a survey by Guidotti et al. (2018), which found that three out of 55 methods used data points. All but one method uses either decision rules or decision tree to explain model internals. The one method in (Olah et al., 2018a), used neural network feature visualization.

Explanation			Explanator			Info.		Personalization				Reference
Properties			Type			Collect-		Granulari		Automati		
					ion		ty		on			
Complexity	Prio. Features	Presentation	Attribution	Data Point	Model Internals	Implicit	Explicit	Individual	Category	Automatic	Manual	
	Pı	Ь	,		M					,		
✓	-	-	-	-	✓	-	✓	-	(✔)	√	-	(Lage et al., 2018)
✓	-	-	-	-	✓	-	-	✓	-	-	✓	(Wang et al., 2016)
✓	✓	-	✓	1	✓	1	-	-	(✔)	✓	-	(Ribeiro et al., 2018)
√	√	-	ı	ı	√	-	ı	-	(✔)	√	-	(Narayanan et al., 2018)
✓		✓	-	-	✓	-	-	-	(✔)	✓	-	(Paulheim, 2012)
√	✓	1	1	1	✓	-	ı	-	(✔)	√	-	(Fürnkranz et al., 2018)
-	✓	1	√	1	-	✓	ı	-	(✔)	√	-	(Ross et al., 2017)
✓	-	-	-	√	ı	1	ı	ı	ı	ı	-	(Li et al., 2017)
✓	-	-	-	-	✓	-	-	-	(✔)	✓	-	(Wu et al., 2017)
-	✓	✓	✓	-	-	✓	-	✓	-	✓	-	(Chen et al., 2018)
-	✓	✓	✓	-	✓	✓	-	✓	-	✓	-	(Chang et al., 2016)
-	✓	-	✓	-	-	✓	-	✓	-	✓	-	(Zhang et al., 2014)
-	-	✓	✓	-	✓	-	✓	✓	-	-	✓	(Olah et al., 2018a)
✓	✓	-	✓	-	✓	-	-	-	(✔)	√	-	(Ribeiro et al., 2016)
✓	-	-	ı	ı	✓	-	ı	-	✓	✓	-	(Lim et al., 2009)
-	✓	-	✓	-	-	-	-	-	(✔)	✓	-	(Dhurandhar et al., 2018)
✓	-	✓	-	-	✓	-	✓	✓	-	-	✓	(Sokol and Flach, 2018)
-	✓	✓	-	1	✓	√	1	-	-	-	-	(Zhang et al., 2017)
✓	-	-	-	-	✓	-	-	-	-	-	-	(Altendorf et al., 2005)
√	-	-	√	1	✓	-	-	-	1.	1	-	(Quijano-Sanchez et al., 2017)

Table 1. Work on explanations in machine learning categorized using concepts relevant to personalization. The \checkmark and - symbols indicate whether the column applies or not. (\checkmark) indicates that the paper only addresses one member of a categorization.

Implicit information collection is common in recommender systems (Chang et al., 2016; Chen et al., 2018; Quijano-Sanchez et al., 2017; Zhang et al., 2014). On the other hand, interactive explanation interfaces (Olah et al., 2018a; Sokol and Flach, 2018) incorporate manual adjustments by the explainee, which may be seen as explicit information collection. Other works in machine learning explanations used feedback from human subjects to improve explanation interpretability. For example, using

explanations from experts as an additional model constraint (Ross et al., 2017). Lage et al. (2018) asked a user to evaluate multiple models for explanations. User were supposed to learn to solve the task, i.e. image classification based on the explanations provided. The model giving the explanations that resulted in highest prediction accuracy by users was chosen.

Multiple works mention some form of personalization. Group personalization is mostly done for only one member of a category, for example, evaluating the method on non-experts on machine learning (Ribeiro et al., 2016) or domain experts (Wu et al., 2017). In contrast, Lim et al. (2009) differentiates explainees by their prior knowledge on the explanation method, while Quijano-Sanchez et al. (2017) use personality as one of their explainee categories. As for those which addressed individual personalization, they are either: i) allowing only manual personalization or ii) they are recommender systems explanations. Manual personalization is enabled either via explanation interfaces (Olah et al., 2018a; Sokol and Flach, 2018) or allowing the incorporation of Bayesian priors (Wang et al., 2016). Explanations for recommender systems are often personalized due to the nature of the task (and the training data). For example, reviews from individuals (Zhang et al., 2014) or browsing activities (Chang et al., 2016) might be required to train the machine learning algorithm and information from the training data is also used to create the explanations. In this case, explicit knowledge extraction on the explainees is not required to personalize the explanations.

To summarize, a systematic treatment of personalized explanations on a conceptual level is absent. Furthermore, existing methods do not cover the entire design space of existing explanation methods, e.g. automatic personalization techniques using explicit information collection have not been developed for machine learning in general for both individuals and categories. This is despite the acknowledgement that an explanation's interpretability may vary considerably between explainees (Ras et al., 2018).

5 Explainee Information

We describe what information can be collected on an explainee and how to obtain this information.

5.1 Collectable Explainee Information

Our synthesis of work on personalization and explanation in machine learning yielded four categories of explainee information:

- Prior knowledge: What an explainee knows
- Decision information: What information an explainee uses for decision making
- Preferences: What an explainee likes and prefers
- *Purpose*: What the explanation is used for

Prior knowledge is partitioned into machine learning knowledge and task domain knowledge:

Machine Learning Knowledge refers to the users' expertise regarding the machine learning method to be explained. One might distinguish them based on their roles such as machine learning engineers or end users, implying a certain level of knowledge (Ras et al., 2018). They describe different levels of deep neural network (DNN) knowledge:

- Knowledge about detailed mathematical theories and DNNs principles.
- Knowledge to train and integrate DNN model into a final application.
- No DNN knowledge, i.e. neither theories nor implementation.

Task Domain Knowledge refers to the users' domain knowledge on the task at hand, e.g. a doctor or a patient using a disease recognition system (Doshi-Velez and Kim, 2017). The nature of the user's expertise influences what level of sophistication they expect in their explanations. For example, domain experts may expect or prefer a somewhat larger and sophisticated model—which confirms facts they know—over a smaller, more opaque one (Lavrač, 1999).

Decision information refers to the information utilized by an explainee when she performs the machine learning task. The information might be rooted in domain knowledge but it might also stem from machine learning or general knowledge or experiences. It is one of the most important criteria for interpretability of explanations (Miller, 2017), namely coherence with prior beliefs. For example, for an image recognition task decision information could be which parts of the image the user would have used to classify that image. This relates to the notion that explanations are selected (Miller, 2017), i.e. when humans provide explanations, they first select what they see as the most relevant causes among all possible causes.

Decision information might be gathered at different levels, i.e. training data and feature level. One might ask an explainee what data samples justify his explanations the most. For example, two doctors might have been exposed to the same patient information during their training, but they might assign difference relevance to patient cases. Extracted features from the data by an individual (and their importance) for decision making also constitutes decision information. For instance, a person might deem colors of objects more important than shapes in image recognition.

Decision information might be collected before any explanation have been made or afterwards, e.g. using feedback or answers to questions on the computed presentations might be used in an iterative manner to improve explanations (Fails and Olsen Jr, 2003) as shown in Figure 1.

Preferences refers to a subjective prioritization of options of an explainee that are not necessarily relevant for any objective measure of the explanation quality such as objective interpretability. But they might strongly impact a person's feeling towards an explanation or her acceptance (plausibility). Preferences include, for example, information such a user's importance rating or constraints with respect to the desiderata of the model (e.g. level of privacy a user wishes to maintain), the desired level of detail of the explanation, the time or effort a user wants to invest to obtain in understanding the explanation, presentation form and employed line of reasoning (e.g. explaining based on prototypes or using general rules).

Purpose refers to the intended use of an explanation. Prior work on explanation has derived purpose based on functional rules (Ras et al., 2018), e.g. end user, developer or data subject. Lipton (2016) lists reasons why machine learning interpretability is desired, namely *trust*, *causality*, *transferability*, *informativeness*, and *fair and ethical decision making*. The purpose might also be seen as obtaining an answer to explanatory questions, i.e. What, How and Why (Miller, 2017). Explainable artificial intelligence presented in (Adadi and Berrada, 2018) mentions justify, control, improve and discover. With respect to personalization, we add the goal of *persuasion*, which aims at changing someone's beliefs through reasoning and argument. Persuasion is a common theme in recommender systems (Cremonesi et al., 2012).

Further information that can be found in the literature on personalization such as "prior experience with the system" might also be utilized.

5.2 Obtaining Explainee Information

Preferences can be elucidated using multiple techniques ranging from traditional means to computer aided methods (Chen and Pu, 2004). Extracting machine learning and task domain knowledge as well as decision information can be done using knowledge extraction methods (Hoffman et al., 1995; Liou, 1992). The techniques differ strongly based on whether the required information is tacit or explicit. A person might find it difficult to express tacit knowledge, e.g. to identify what she utilizes in her decision process. But it might be relatively easy for a person to judge whether she is an expert on a topic or not (explicit knowledge) or state the purpose of the explanation. Elicitation techniques empirically analyzed in (Dieste and Juristo, 2011) are classified based on (Hoffman et al., 1995) into three categories as follows:

• Analysis of familiar tasks – investigating what explainees do when performing tasks under their usual condition, e.g. protocol analysis, unobtrusive observation, or simulated task.

- *Interviews* asking the explainees about what they do. This can be done through unstructured or structured interviews.
- Contrived techniques investigating what explainees do when performing modified tasks, e.g. scaling, sorting, or hierarchical structuring. An exemplary technique is the repertory grid (McGeorge and Rugg, 1992). It can be applied to the one of the best studied machine learning problems namely classification. The goal is to elucidate information on how people classify elements by first selecting a group of elements representing a relevant aspect of the domain. Significant constructs are identified by presenting three elements and asking how to are similar and thus different from the third.

Interviews are suitable to elicit explainee's explicit knowledge. Eliciting tacit knowledge for explainee modelling, however, can be done with machine learning techniques (Webb et al., 2001). In this case, analysing familiar tasks and contrived techniques can be used to classify these machine learning techniques. We presented machine learning techniques according to this classification in Table 2.

Category	Technique					
Analysis of familiar tasks	Usage log, e.g. web usage (Geng and Tian, 2015), mouse cursor movement (Schneider et al.), browser activity (Chang et al., 2016).					
	Protocol analysis, e.g. sharpening important parts of an image (Das et al., 2017).					
Contrived techniques	Sorting, e.g. assigning document relevance (Maddalena et al., 2016), annotating video (A. Prest et al., 2012), selecting images of a certain concepts (Kim et al., 2018), annotating machine learning explanation (Ross et al., 2017).					

Table 2. Exemplary Machine learning techniques to elicit tacit knowledge

While (Hoffman, Shadbolt, Burton and Klein, 1995) have a strong emphasis on knowledge elicitation from experts, other (overlapping) categorizations have been derived for related tasks. For instance, to learn user profiles (Montaner, López and De La Rosa, 2003) distinguish three categories in the context of recommender systems:

- Manual methods refer to methods where the explainee explicitly states the required information.
- Stereotyping refers to extracting explainee information based on group memberships.
- Training set refers to the collection of explainee's execution of tasks relevant to the explained machine learning model.

6 Personalized Explanation Methods

Once explainee information has been collected (Section 5), personalized explanations can be created using a two-step process, namely: i) customizing explanation properties, ii) and generating the personalized explanation. The process might be iterative, involving collecting additional explainee information based on feedback on the generated explanations (Figure 1).

6.1 Customizing explanation properties

A personalized explanation is obtained by adjusting explanation properties making use of explainee information and taking into account the explanator type as illustrated in Table 3. We first discuss how explainee information affects each explanation property. Then, we elaborate on how to adjust to the explanator type.

Explainee information relevant to personalize an explanation's **complexity** are machine learning knowledge, task domain knowledge, and explanation purpose. More complex explanations may suit more knowledgeable explainees. Explanation complexity might also depend on the purpose of the

explanation. For example, a data scientist might look for a detailed explanation for debugging and a simpler one for presenting findings to non-experts.

Prioritization of decision information can be done, e.g. according to the explainee's task domain knowledge. Using a disease recognition task as an example, doctors might understand more medical terms than patients and two doctors might use different symptoms to diagnose, respectively. A more visual example is given by the saliency map in Figure 2. An attribution technique might highlight certain areas contributing most strongly to the decision, i.e. the body of the bird. A personalized method for users focusing on heads might emphasize more the head detailed characteristics of it such as eyes or beak.





Figure 2. Saliency map using Lucid (Olah et al., 2018b) (left figure) and a possible personalization focusing on heads (own illustration, right figure).

Explainee information on machine learning knowledge and purpose are relevant to personalize the **presentation** of an explanation. For example, using an image saliency map might be enough to convince non-experts of the model's accountability. For machine learning experts who want to improve the model, however, adding feature visualization might be useful.

	Attribution	Data Point	Model Internals
Complexity	Number of features and/or classes. Selection of contributor and target, e.g. feature-feature or input-output.	Number of data points. Categorization of data points, e.g. by class or by prediction certainty.	Size, e.g. depth or length. Feature relationships. Type of representation, e.g. decision tree, decision rules, or feature visualization.
Prioritized Decision Information	Features to present.	Features that most characterize the data points.	Features and feature relationships to present.
Presentation	Selection of visualization technique.	Structuring of the data points.	Selection of visualization technique.

Table 3. Exemplary use of explainee information depending on the explanator type and adjusted properties.

Personalizing complexity on **attribution** explanators is done through adjusting the number of presented contributors, e.g. length of a feature list (sorted by importance), and number of attribution targets, e.g. the number of classes to analyze. The relationships between contributors and attribution target can also contribute to complexity, e.g. attribution between intermediate layers or between input and output for a neural network explanation. Moreover, an attribution explanator can be personalized by using explainee's relevant features in prioritizing decision information, e.g. selecting explainee's relevant features in the case of ties on features importance as shown in Figure 2. Personalizing the presentation is done through the selection of visualization technique, e.g. highlighting words in sentences or a word list.

An explanator using **data points** may show data points from one or more categories. Categories might be pre-defined such as class labels or based on other information, i.e. predicted class probabilities might

be grouped into "low, medium, high" and out of these groups data points might be chosen. Personalizing complexity is done by adjusting the number of data points, number of categories, and the categories' complexity. To personalize the prioritized decision information, data points can be taken either from the ones provided by the explainee or the ones characterized the most by explainee's relevant features. In terms of presentation, data points can be shown with or without structure. An example for a structured presentation is to lay out the data points on a grid based on their similarities as shown in Figure 3. The t-SNE (van der Maaten and Hinton, 2008) is an embedding of the similarities of data samples in two dimensions. It allows an explainee to understand better what samples the machine learning model considers as similar and dissimilar.



Figure 3. t-SNE visualization for Olivetti face dataset adapted from Supplementary material S9 of van der Maaten and Hinton (2008).

Personalization of **model internals** depends on its representation. Complexity is personalized by adjusting its size, e.g. sparseness of a linear model, and features relations, e.g. presence of conjunctions in a decision rule, to match the explainee's expertise. Additionally, the type of representations also contributes to complexity, e.g. explaining a neural network by feature visualization or its decision tree approximation. Explainee's relevant features can be prioritized by selecting model internals which involves those features. For example, selecting a decision tree which includes explainee's relevant features or providing visualizations of neurons which corresponds to those features. Another example is to select decision rules which are close to the explainee's decision making rules. Presentation is personalized through the selection of appropriate visualization techniques and forms. For example, an explainee may prefer decision rules to be presented in natural language or using imagery as illustrated in Figure 4 (Chen et al., 2018).

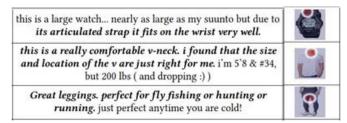


Figure 4. Examples of textual (left) and visual (right) explanations adapted from Chen et al. (2018).

6.2 Post-hoc and intrinsic methods

There are two approaches from interpretable machine learning, namely, intrinsic and post-hoc explanation, illustrated in Figure 5.

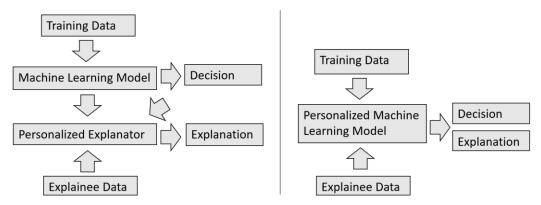


Figure 5. Illustration of possible implementation of intrinsic and post-hoc personalized explanation methods

Intrinsic personalization seeks to find and train machine learning models that optimize two goals at the same time, i.e. solving the task at and providing explanation of the solutions. An intrinsic personalized model learns:

- (i) to use explainee's relevant features in the decision making, and/or
- (ii) concepts with a degree of complexity defined by the explainee.

As such, this approach doesn't address personalization of explanation presentation. An example for the former is presented in (Ross et al., 2017), where they used the neural network's explanation as a constraint in the training phase. Expert annotated images are used as the 'right reasons' for classifying an image. The differences between the experts' and model's explanations are then minimized. In the personalization context, this approach can be adapted by using one annotation source for one model. Wu et al. (2017) regularized a neural network by the depth of its decision tree approximations. Apart from constraining features used and degree of complexity, another approach is personalizing the training data. This may cause the machine learning model to mimic the explainee's decision making process, e.g. as in an explainable recommender system (Zhang et al., 2014).

Post-hoc personalization consists of an explanator method that is independent of the machine learning model solving the task. It provides explanations without altering the machine learning model trained on the original task. It might have access to explainee data that is not use by the machine learning model solving the task. This approach is applicable to personalize all three explanation aspects, i.e. complexity, prioritization of decision information and presentation. For example, in an interface to explain a convolutional neural network (Olah et al., 2018a), the explanatory types, e.g. feature visualizations or saliency maps, can be adjusted directly by the explainee. For example, a decision rule is selected as an explanation among multiple valid decision rules based on its precision (Ribeiro et al., 2018). In terms of personalization, this selection can be based, e.g. on the presence of explainee's relevant features in the rule. Another example is presented in (Chen et al., 2018), here an item recommendation is visually explained by marking a certain parts on the item's image. They personalized the visual explanations by marking item features which are relevant to the explainee, i.e. different explainee with the same recommended item might get different visual explanations.

The two approaches pose different trade-offs to be considered. Personalized explanations from intrinsically personalized models may produce explanations that are more faithful than post-hoc methods.

7 Evaluation of personalized explanation methods

Evaluation of desiderata of explanation methods in general is discussed in (Adebayo et al., 2018; Guidotti et al., 2018; Ras et al., 2018; Ribeiro et al., 2016, 2018). Here we focus on modifications of them towards personalization as well as on criteria that only apply for personalization.

An important aspect of **generalizability** is the range of explainee information a personalization method can incorporate, e.g. whether it can include both user's machine learning knowledge and task domain expertise or not.

As for evaluating **interpretability**, two kinds of measures are formulated in (Fürnkranz et al., 2018): i.) an objective measure of the explanation's capability to aid the explainee in performing a task (comprehensibility), and ii.) a subjective measure of the explainee's acceptance of the explanation (plausibility). The objective part can be evaluated through measuring explainee performance, e.g. the response time and accuracy in simulating a model's decision (Lage et al., 2018; Narayanan et al., 2018; Poursabzi-Sangdeh et al., 2018; Ribeiro et al., 2018). Another objective measure would be measuring the explainee's understanding about the explained model. For example, whether explainees can identify model's incorrect prediction (Poursabzi-Sangdeh et al., 2018). Whereas the subjective measure is often evaluated through explainee rating on aspects such as plausibility, usefulness, surprisingness, nontriviality, trustworthiness, or overall satisfaction (Fürnkranz et al., 2018; Narayanan et al., 2018; Paulheim, 2012). Explainee's acceptance can also be evaluated indirectly. In (Poursabzi-Sangdeh et al., 2018), trust is evaluated by measuring the differences between the model's and explainee's predictions. Another approach is to use the proportion of predictions made by explainees after receiving the explanations, i.e. were they confident enough to make a prediction or not (Ribeiro et al., 2018). A taxonomy of interpretability evaluation is proposed in (Doshi-Velez and Kim, 2017) consisting of application-grounded, human-grounded and functionally-grounded evaluation.

Privacy can be measured using a variety of measures often formulated in terms of what an adversary targeting to obtain confidential information can actually achieve (Wagner and Eckhoff, 2018). It depends on the adversarial model, e.g. whether an adversary has access only to information stored permanently (e.g. on disc) or to temporary information (e.g. in main memory) or whether he can only listen to communication (e.g. Internet traffic) or listen to all keystrokes and mouse movements of a user (Goodrich and Tamassia, 2011). Suitable output measures in our context might be information gain, i.e. how much an adversary learns about the explainee, or uncertainty, i.e. the size of the crowd from each an individual cannot be distinguished from.

Extraction effort can be quantified using time the explainee requires to provide the information. Cognitive load of the explainee to provide information might also be assessed, e.g. using eye-tracking systems (Buettner, 2013) or using mental effort ratings and performance scores (Paas and van Merriënboer, 1993).

8 Conclusion

Developing explainee-centric methods for explaining machine learning methods might significantly enhance interpretability. We believe that better explanations are not just relevant due to legal pressure such as the GDPR or to improve existing machine learning models, but also since they create new possibilities for emerging fields such as "machine teaching", i.e. machine teaching humans.

Despite some effort towards this goal, there are significant gaps as indicated in our review. We discovered that explicit information collection from explainee is rarely done. Furthermore, our conceptualization revealed that personalized explanation method differ from conventional explanation methods in aspects such as taking into account an explainee's privacy as well as the information collection effort from explainees.

By summarizing, combining and extending ideas from multiple disciplines, we hope that our work can help to guide researchers in the development and understanding of personalized explanation methods in the field of machine learning and related fields such as artificial intelligence.

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