GAM CHANGER: Editing Generalized Additive Models with Interactive Visualization

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ABSTRACT

Recent strides in interpretable machine learning (ML) research reveal that models exploit undesirable patterns in the data to make predictions, which potentially causes harms in deployment. However, it is unclear how we can fix these models. We present our ongoing work, GAM CHANGER, an open-source interactive system to help data scientists and domain experts easily and responsibly edit their Generalized Additive Models (GAMs). With novel visualization techniques, our tool puts interpretability into action—empowering human users to analyze, validate, and align model behaviors with their knowledge and values. Built using modern web technologies, our tool runs locally in users’ computational notebooks or web browsers without requiring extra compute resources, lowering the barrier to creating more responsible ML models. GAM CHANGER is available at https://interpret.ml/gam-changer.

INTRODUCTION

It is crucial to understand how machine learning (ML) models used in high-stakes settings (e.g., healthcare, finance, and criminal justice) make predictions (Fig. 2A). Recently, researchers have made substantial efforts to make ML models interpretable [e.g., 10, 22, 26]. Yet, not as much research focuses on what do we do with these model explanations. In practice, data scientists and domain experts often compare model explanations with their knowledge [ 18]. If the model uses expected patterns to make predictions, people will feel more confident to deploy it to solve real problems. Sometimes, ML interpretability can uncover hidden relationships in the data—helping people gain insights about the problems they want to tackle.

Other times, however, ML interpretability reveals models’ exploitation of dangerous patterns in the data to make predictions.

Figure 1: GAM CHANGER empowers domain experts and data scientists to easily and responsibly align model behaviors with their domain knowledge and values, via direct manipulation of GAM model weights. For example, the GAM Canvas enables doctors to interpolate the predicted risk of dying from pneumonia to match their domain knowledge of a gradual risk increase from age 81 to age 87. GAM CHANGER promotes accountable editing and elucidates potential tradeoffs induced by the edits. The Metric Panel provides real time feedback on model performance. The Feature Panel helps users identify characteristics of affected samples and promotes awareness of fairness issues. To enable reversible transparent model edits, the History Panel allows the doctor to compare and revert changes, as well as document their motivations and editing contexts.
These patterns might be an accurate reflection of real-world phenomena, but leaving them untouched can cause serious harm in deployment. For example, ML models that decide mortgage approvals exhibit biases against loan applicants of color [23]. These biases reflect and are inherited from the real world [3]. In healthcare, state-of-the-art models show that having asthma lowers the risk of dying from pneumonia (Fig. 2B), where researchers suspect it is because asthmatic patients receive care earlier [10]. If we use this flawed model to make hospital admission decisions, asthmatic patients are likely to miss the care they need. Interpretability helps us identify these dangerous patterns, but how can we take a step further and use model explanations to improve (Fig. 2C) ML models?

To answer this question, we are developing GAM Changer (Fig. 1): an interactive visualization system that empowers data scientists and domain experts to easily and responsibly edit the weights of generalized additive models (GAMs), the state-of-the-art interpretable ML model for tabular data [10, 16]. We iteratively design this tool by continuously integrating feedback from ML and human-computer interaction (HCI) researchers, data scientists, and doctors. In this ongoing work, we contribute:

- **GAM Changer**, a novel interactive system that empowers data scientists and domain experts to edit GAMs to align model behaviors with their knowledge and values. Advancing over prior visualization work for interpretable ML [17, 30], our tool is the first system that enables users to directly modify ML models with model explanations through interactive visualization.

- **Responsible and novel visualization design** through a participatory and iterative process with doctors and data scientists. Inspired by popular image editing and illustration tools, GAM Changer adapts familiar Direct Manipulation [28] user interfaces to edit complex ML models. Accessible model editing empowers users to exercise their human agency but demands caution, as modifications of high-stake models have serious consequences. Therefore, guarding against harmful edits is our top design priority: we leverage **continuous feedback and reversible actions** to elucidate editing effects and promote accountable edits.

- **An open-source**, web-based implementation that broadens people’s access to creating more accountable ML models and exercising their human agency in a world penetrated by AI systems. We develop GAM Changer with modern web technologies such as WebAssembly². Therefore, anyone can access our tool directly in their web browser or computational notebooks and edit ML models with real datasets at scale. For a demo video of GAM Changer, visit [https://youtu.be/2gVSopSeJ8](https://youtu.be/2gVSopSeJ8).

We hope our work helps emphasize the importance of human agency in responsible ML research, inspiring future work in human-AI interaction and actionable ML interpretability.

### 2 BACKGROUND AND RELATED WORK

Generalized additive models (GAMs) have emerged as one of the most popular model classes among today’s data science community. GAMs’ predictive performance is on par with more complex, state-of-the-art models, yet GAMs remain simple enough for humans to understand its decision process [11]. Given an input $x \in \mathbb{R}^M$ with $M$ features and a target $y \in \mathbb{R}$, a GAM with a link function $g$ and shape function $f_j$ for each feature $j \in \{1, 2, \ldots, M\}$ can be written as:

$$g(y) = \beta_0 + f_1(x_1) + f_2(x_2) + \cdots + f_M(x_M)$$  \hspace{1cm} (1)$$

The link function is determined by the task. For example, in binary classification, $g$ is logit. In Equation 1, $\beta_0$ represents the intercept constant. There are many options for the shape functions $f_j$, such as splines [16], gradient-boosted trees [10], and neural networks [1]. Some GAMs also support pair-wise interaction terms $f_{ij}(x_i, x_j)$. Different GAM variants come with different training methods, but once trained, they all have the same form. The interpretability and editability of GAMs stem from the fact that people can visualize and modify each feature $x_j$’s contribution score to the model’s prediction by inspecting and adjusting the shape function $f_j$. The contribution score is measured by the output of $f_j(x_j)$. Since GAMs are additive, we can edit different shape functions independently.

Besides glass-box models like GAMs that are inherently interpretable [e.g., 20, 33], ML researchers have developed post hoc explanation methods to interpret any black-box models [e.g., 22, 26]. HCI researchers study how to communicate model explanations [19], and develop visual analytics systems to help users interactively analyze ML models [17, 30, 31]. Our work advances the interpretable ML landscape in making interpretability actionable. Although research shows that modifying model outputs can lead to greater trust and better human-AI teaming performance [14], there has been little work on how we can leverage interpretability to adjust models. Most existing work [4, 5, 29] relies on black-box models and post hoc explanations—users can only affect a small subset of model behaviors and modifications are likely to have unknown effects. Grounded on accurate and complete interpretations provided by glass-box models, GAM Changer is the first framework that enables users to have total control of their model behavior and recognize the editing effects, so that they can easily and safely improve ML models in solving high-stake problems.

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²GAM Changer code: [https://github.com/interpretml/gam-changer](https://github.com/interpretml/gam-changer)

²WebAssembly: [https://webassembly.org](https://webassembly.org)

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**Figure 2:** A Doctors often hesitate to trust ML models as they cannot interpret how the models make predictions. B With interpretable ML, researchers and doctors discover models can learn unexpected patterns, potentially causing harm in deployment. C Model editing turns interpretability into actions, enabling doctors to repair ML models and align model behaviors with their domain knowledge.
3 SYSTEM DESIGN AND IMPLEMENTATION
To lower the barrier to controlling ML behaviors, GAM CHANGER employs familiar direct manipulation user interface patterns to edit the parameters of GAMs (§ 3.1). By providing real-time feedback about the model performance (§ 3.2) and potential effect parity across features (§ 3.3), our tool encourages data scientists and domain experts to edit models responsibly. All edits are reversible, and users can document and compare their edits (§ 3.4). To start GAM CHANGER, users can use our provided functions to extract GAM parameters from a popular GAM library [25] and test samples from the data (either a validation set or a subset of training data).

3.1 GAM Canvas
The GAM Canvas (Fig. 1A) is the primary view of GAM CHANGER, where we visualize one input feature $x_j$’s contribution to the model’s prediction by plotting its shape function $f_j(x_j)$. As GAMs support continuous and categorical features, as well as their two-way interactions, we design separate visualization for each variable type, featuring line chart, bar chart, heatmaps, and scatter plots (Fig. 3). Users can use the feature selection drop-down to smoothly transition across features. When started, the tool shows the feature with the highest importance score, computed by the weighted average of a feature’s absolute contribution scores.

Shape function visualizations. Modern GAMs usually discretize continuous variables into finite bins, so that shape functions can easily learn complex non-linear relationships. Therefore, the output of shape functions is a continuous piecewise constant function. We use a dot to show the start of each bin and a line to encode the bin’s constant score (Fig. 1A). For categorical features, we represent each bin as a bar whose height encodes the bin’s score (Fig. 3B). To help users keep track of their edits, we color code the lines and bins by the editing sequence: the original function, function in the last edit, and the current function. We also use histograms to visualize the bin count distribution in the training data.

Contribution baseline. To help users more easily interpret GAMs, we re-center the contribution scores by adjusting the intercept constant $f_0$, so that the mean prediction for each feature has a zero score across the training data. Therefore, a positive contribution score suggests that the feature positively affects the prediction, and vice versa. Consider a GAM trained to predict house prices (Fig. 3A), if the living area is larger than 2000 square feet, it increases the predicted house price, while areas lower than 2000 decrease the predicted value compared with average. We highlight the 0-baseline as a thick dashed line in our visualizations.

Interaction modes. In the GAM Canvas, users can switch between Move Mode and Selection Mode by clicking the mode toggle button. In the Move Mode, users can use zoom-and-pan to control their view portion and focus on analyzing an interesting region in the GAM visualization. In the Selection Mode, users can use marquee selection (Fig. 1A) to pick a subset of bins (or bars for categorical features) to edit.

Editing tools. Once a region of the shape function is selected, the Context Toolbar (Fig. 4) appears: it affords a variety of editing functions, represented as icon buttons, to meet editing needs in different scenarios. Users can click the buttons to change the shape function in the selected regions. For example, a user can click the monotonically increasing button $\nearrow$ to transform an interval of the shape function into a monotonically increasing function. In some settings, such monotonicity may be required, for example to control the model’s inference in some regions.
by regulations for financial ML models. Internally, GAM CHANGER fits an isotonic regression [2] weighted by the bin counts, and uses it to determine a new shape function that meets the regional monotonicity constraint with minimal changes. The user can view the number of samples in the selected bins and a description of their edit on the bottom Status Bar (Fig. 1A). Then, they can click the check icon ✔ to “commit” (§ 3.4) the change if they are satisfied with this edit, or click the cross icon ✗ to discard the change.

3.2 Metric Panel
One of our design priorities is to promote responsible editing. To help users identify the effects of their edits, the Metric Panel (Fig. 1-B1) provides real-time and continuous feedback on the model performance. For a binary classifier, we present a confusion matrix and use bar plots to encode the model’s accuracy, balanced accuracy, and the Area Under the Curve (AUC). Similarly, for a regression model, we report root mean squared error, mean absolute error, and mean absolute percentage error. Also, we use the same color codes of shape functions in the GAM Canvas to describe the performance of the original model, the model from the last edit, and the current model.

Besides monitoring global metrics that are computed on all test samples, users can change the metric scope by clicking the Scope Switch. For example, in the Selected Scope, the Metric Panel only reports the model performance of samples that are in the selected region. It helps users to focus on samples that are affected by their edits. In the Slice Scope, users can slice the samples by selecting a level of a categorical variable, e.g., the female level of the gender variable. Then, performance metrics are computed on the test samples that belong to the selected subgroup. Allowing users to study the model performance on different slices of the dataset provides an opportunity to probe for equitable editing across different groups [31].

3.3 Feature Panel
Feature correlations and confounders convolute ML interpretation [24]. Glass-box models like GAMs can help people identify missing confounders by revealing the effects of multiple features [27]. Due to space constraints, in the GAM Canvas users can only inspect and edit one feature at a time. Therefore, we design the Feature Panel (Fig. 1-B2, Fig. 5) to help users gain an overview of correlated features as well as their distributions and elucidate potential editing impact disparities. Inspired by visualization techniques context+focus [9] and brushing+linking [8], we develop linking+reordering—a simple method to identify correlated features.

Once a user selects an interval of the shape function in the GAM Canvas (Fig. 5-A), we look up affected samples and their associated bins across all features. For each feature, we compare the bin count frequency of all training data and the frequency of the selected samples by measuring the ℓ2 distance between these two frequency vectors. Then, we plot two frequency distributions in an overlaid histogram for each feature, and sort all histograms in descending order of the distance scores (Fig. 5-B). The intuition is that if two features x1 and x2 are independent, then samples selected from an interval in x1 should have a distribution similar to the training data distribution in x2, and vice versa. Therefore, correlated features will be on top of the sorted histogram list. Our linking+reordering technique allows users to interactively and quickly identify local correlations across features, even between continuous and categorical features. By observing correlated features and their distributions, users can identify potential editing effect disparity: for example, editing in Fig. 5 would disproportionately affect newer houses.

3.4 History Panel
In GAM CHANGER, users can undo and redo their edits by clicking the buttons in the bottom Status Bar or using keyboard shortcuts. Reversible model editing promotes accountable modifications, as users can easily fix their editing mistakes. To empower users to quickly and easily trace, compare, and revert the changes they have made, the History Panel tracks all edits and shows each one as an information card in a list (Fig. 1-B3). Inspired by the version control system Git3, we model each edit as a commit—a snapshot of the underlying GAM. Each commit has a timestamp, a unique identifier, and a commit message.

Once an edit is committed, we automatically generate an initial commit message to describe the edit; users can update the message in the History Panel to further document their editing motivation and context.

Figure 5: A On a GAM trained to predict house price, a user selects bins representing high house quality in the GAM Canvas. B For categorical variables, the Feature Panel shows that selected houses disproportionally have better exterior and kitchen quality and locate in certain neighborhoods. C For continuous variables, the year built and garage area also highly correlate with the house quality.

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3Git: https://git-scm.com
In addition, users can browse the model evolution by clicking the Check-out button to load previous GAM versions. Users can also discard edits by clicking the Delete button. Once users finish editing, they can click the Save button in the Status Bar to save the latest GAM along with all editing history, which can be used for deployment or future continuing editing. Before saving the model, GAM Changer requires users to examine and confirm all edits by clicking the Confirm button. It helps users identify editing mistakes and promote accountable editing.

3.5 Web-based, Open-source Implementation

GAM Changer is a modern web-based interface built with D3.js [6]. It is compatible with the popular GAM library InterpretML [25]; users can easily export GAMs to edit and load modified GAMs. We use WebAssembly to accelerate in-browser computations, such as GAM inference and isotonic regression. It makes our tool scalable: all computations are real-time with less than 5k test samples, and the sample size is only bounded by the browser memory limit. Users can also use our tool directly in their computational notebooks—popular workflow for ML development [34]. With modern web technologies, our tool makes it accessible for domain experts and data scientists to locally and privately edit GAMs with minimal coding. We open source GAM Changer and all WebAssembly components, so future researchers and designers can easily generalize our design and implementations to other forms of model editing.

4 USAGE SCENARIO

We present a hypothetical usage scenario to illustrate how GAM Changer could potentially help doctors and data scientists discover and fix harmful behaviors in a GAM that predicts a patient’s risk of dying from pneumonia. In this usage scenario, all metrics reported are based on models trained on a dataset of 14,199 pneumonia patients [10]. The dataset has 46 features: 19 features are continuous, while 27 are categorical. The outcome variable has a binary value: 1 if the patient died of pneumonia and 0 if they survived.

Model interpretation. Users—in this case, doctors and data scientists—can easily set up GAM Changer in a web-based interface with drag-and-drop or directly in their computational notebooks. age is the first feature GAM Changer presents to users, as it has the highest importance score across all features. In the GAM Canvas (Fig. 6A), the x-axis ranges from 18 to 106 years old. The y-axis encodes the predicted risk score (log odds) of dying from pneumonia. It ranges from a score of -0.4 for patients in their 20s to 0.5 for patients in their 90s. A negative risk score represents lower risk than the average patients, while a positive score means higher risk than the average patients. The light blue background below the line plot encodes the model’s uncertainty, which is strongly correlated with the training sample size in different age ranges, as shown in the histogram at the bottom of the GAM Canvas.

By observing the shape function visualization (Fig. 6A), users can see that the model predicts younger patients to have a lower risk than elder patients. The predicted risk rapidly increases when patients get older than 67. However, the predicted risk suddenly plunges when the age passes 100—leading to a similar risk score as if the patient is 30 years younger! This prediction pattern also exists in the XGBoost and Random Forest models, but is harder to detect since these models are black-box.

There are several hypotheses to explain this dangerous behavior across ML models. For example, it might be due to outliers in this age range, especially the range has a small sample size (shown in the histogram), or patients who live this long might have “good genes” to recover from pneumonia. To identify the true impact of age on pneumonia risk, additional causal experiments and analysis are needed. Without robust evidence that people over 100 are truly at lower risk, many doctors may fear that they would be injuring patients by depriving needy older people of care, and violating their primary obligation to do no harm. Therefore, doctors would like to fix this pattern. A conservative remedy is to set the risk of older patients to be equal to that of their slightly younger neighbors.

Editing continuous features. To do that, a doctor can select the bins that represent age above 98 years old through drawing a bounding box in the GAM Canvas (Fig. 6-A). Then, the Context Toolbar appears, where the doctor can click the Align to The Left button (Fig. 6-B1). With a smooth animation, GAM Changer raises the bin that encodes age above 100 vertically, so that it has the same risk score as the first bin on the left (age 98–100). From the Metric Panel, the doctor can see that the accuracy decreases by 0.0004 when evaluating all 5000 test samples in the Global Scope (§ 3.2). To focus on the model performance on the affected 28 samples, the doctor can switch to...
the Selected Scope: the confusion matrix shows that the edit causes the model to mis-classify two negative cases as false positives.

The accuracy drop is negligible, as any change to an optimized model is likely to hurt the performance on the training data; the edit is likely to make the model generalize better to unseen data. To learn more about these 28 patients who would be affected by the edit, the doctor can open the Feature Panel, which shows that gender is the second most correlated categorical feature with the selected age range. It means patients who are affected by this edit are disproportionately female—it makes sense because on average women live longer than men. By identifying and showing the correlated features, the Feature Panel promotes users to be aware of potential fairness issues during model editing.

Besides the problematic drop of predicted risk for older patients, the risk suddenly rises around age 86 (Fig. 6A). After converting the risk score from the log-odds space to probability space, the predicted likelihood of dying from pneumonia increases by 4.8% when the age goes from 86 to 87! Similar to the previous discussion, this model behavior can cause 81–86 years old patients miss the care they need. To fix this pattern, the doctor can select the region from age 81 to 87 and click the Interpolate button \(\bullet\) (Fig. 6-B2). Then, GAM CHANGER would linearly interpolate risk scores in the selected range, so that the model behavior matches doctors’ domain knowledge of a gradual risk increase from age 81 to 87.

Editing categorical features. In addition to continuous features, GAM CHANGER also allows users to edit categorical features. For example, the GAM Canvas of the binary feature asthma shows that the model predicts asthmatic patients to have lower pneumonia risk than non-asthmatic patients (Fig. 7A). This model behavior is likely to go against doctors’ knowledge and experience. A conservative option to modify this behavior is to remove the predictive effect of having asthma, so that the model predicts asthmatic patients to have an average risk. To do that, a doctor can select the bar in the GAM Canvas and clicks the Delete button \(\bullet\). It would increase the risk score of having asthma from \(-0.2\) to \(0\). Then, the doctor can document the edit motivation and context for future references by leaving a comment, such as “Conservative way to fix the wrong risk score of having asthma,” in the History Panel. Finally, after reviewing and confirming all edits by clicking the Confirm button \(\bullet\), the doctor can save the new model and edit history.

5 ONGOING WORK AND CONCLUSION

With a responsible and familiar design, GAM CHANGER enables domain experts and data scientists to turn ML interpretability into actions. From the usage scenario (§ 4), we can see that model editing is an iterative and complex process, and it is new to many ML researchers and practitioners. To help GAM CHANGER users create more accountable ML models, our ongoing work includes:

- Evaluate the usability of GAM CHANGER by running an observational user study with data scientists.
- Case studies on real datasets with doctors and data scientists. We will deploy edited GAMs in healthcare settings and monitor their performance in the real life.
- Distill guiding principles of when we should edit ML models and how to edit them in different scenarios.

Limitations. We design GAM CHANGER to guard against harmful edits by providing users with continuous feedback (§ 3.2 and 3.3), as well as transparent and reversible edits (§ 3.4). However, it does not guarantee to prevent users from overfitting the model, injecting harmful bias, or maliciously manipulating model predictions. This potential vulnerability warrants further study on how to audit and regulate model editing. We will deploy GAM CHANGER with caution, monitor its impact, and continuously improve the design to promote responsible editing.

Conclusion. GAM CHANGER takes steps toward democratizing responsible ML. Through applying interactive visualization techniques, GAM CHANGER provides an easy-to-use interface that empowers domain experts and data scientists to not only interpret ML models, but also align model behaviors with their knowledge and values. We hope our work helps emphasize the importance of human agency in responsible ML research, inspiring future work in human-AI interaction and actionable ML interpretability.

6 ACKNOWLEDGEMENT

The first two authors were summer interns at Microsoft Research. We especially thank Scott Lundberg for insightful conversations. We are also grateful to Steven Drucker, Adam Fourney, Saleema Amershi, Dean Carignan, Rob DeLine, and the InterpretML team for their helpful feedback.

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