Explanation-Based Tuning of Opaque Machine Learners with Application to Paper Recommendation

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Abstract

Research in human-centered AI has shown the benefits of machine-learning systems that can explain their predictions. Methods that allow users to tune a model in response to the explanations are similarly useful. While both capabilities are well-developed for transparent learning models (e.g., linear models and GA²Ms), and recent techniques (e.g., LIME and SHAP) can generate explanations for opaque models, no method currently exists for tuning of opaque models in response to explanations. This paper introduces LIMEADE, a general framework for tuning an arbitrary machine learning model based on an explanation of the model's prediction. We apply our framework to Semantic Sanity, a neural recommender system for scientific papers and report on a detailed user study, showing that our framework leads to significantly higher perceived user control, trust, and satisfaction.

1 Introduction

Guidelines for human-AI interaction dictate that machine learning (ML) systems should be able to explain their predictions and accept corrections [5]. Both explanation and tuning methods exist for transparent models, such as linear classifiers or generalized additive models (GA²Ms) [15]. But since opaque models, such as boosted decision forests and deep neural networks, often provide higher performance, many researchers have developed methods for generating explanations of an opaque ML model — typically creating a transparent approximation to the opaque model, called an explanatory model [18]. While these explanatory models have seen significant adoption, the problem of interpreting user feedback remains: how can one translate users' requested changes, which are expressed in terms of features in the explanatory model, back into changes to the underlying opaque model?

In this paper, we present LIMEADE, a general technique for tuning an arbitrary, opaque machine learning model in response to feedback on an explanation of its behavior. As

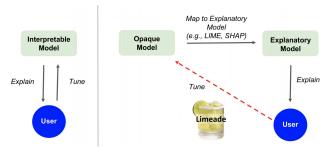


Figure 1: An interpretable model such as a GA²M (left) is by definition explainable and tunable [15]. With an opaque model (right), methods such as LIME and SHAP enable the user to receive an approximate explanation; however, no such method enables the user to tune the opaque model directly. LIMEADE provides this mechanism, completing the loop.

shown in Figure 1, our approach builds upon explanatory approaches such as LIME [43] and SHAP [37] that describe the behavior of a model local to a given instance. Given a trained model and an instance to be classified, these post-hoc approaches output an explanation in the form of a weighted list of the interpretable features (often distinct from the features utilized in the opaque model) that influence the instance's classification. With LIMEADE, a user can then provide feedback on the explanation in order to tune the original, opaque model. For example, suppose that a user is using a deep neural image classifier that consumes raw pixel values to predict if an image contains a husky; suppose further that the explanatory approach generates an explanation in terms of superpixels [43]. A user may want to reinforce that a superpixel containing a patch of grey fur is a positive indicator, but mark the superpixel with snow as a spurious confound. LIMEADE tunes the opaque model in response by retraining on pseudoexamples, generated and labeled according to the user's feedback on the explanation.

Since studies involving Mechanical Turk workers, who are instructed to care about the ML model in question, can be misleading, we instead evaluate LIMEADE with real users who truly care about improving the accuracy of their ML models. Specifically, we incorporated LIMEADE within Semantic Sanity, a neural recommender for research papers with hundreds of users, that enables users to curate feeds of recent computer science research. Although Semantic Sanity

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¹https://s2-sanity.apps.allenai.org

is powered by an opaque neural model, it explains recommended papers by listing influential paper terms, and the user can mark these terms as of interest or not. We evaluate LIMEADE on the website through user studies and log studies. Our work reveals a fundamental tension between providing the most faithful explanations (by greedily selecting the most influential features) and providing the best affordances for tuning (by providing a variety of possible refinements). We call this the *explanation-action tradeoff*.

In summary, our contributions are:

- 1. We introduce LIMEADE, a general framework that enables a user to tune an arbitrary, opaque learning model in response to an approximate explanation.
- We apply LIMEADE by building Semantic Sanity, a publicly-available computer science paper recommendation platform that allows users to train, explain, and adjust personalized research feeds.
- 3. Studying the logs of 300 users of Semantic Sanity, we expose the explanation-action tradeoff, a tension between using canonical greedy explanation approaches vs. providing a more diverse set of explanations with better affordances for tuning.
- Through a user study of Semantic Sanity with 21 participants, we demonstrate that our implementation of LIMEADE improves user perceived control, trust, and satisfaction.

2 Previous Work

2.1 Explainability

Developing methods for understanding the reasons behind a model's classifications is an essential part of machine learning. Models such as linear models and decision trees benefit from being intrinsically interpretable but are limited in performance on many tasks. In contrast, opaque models such as neural networks are ubiquitous due to high performance but present difficulties precisely because they are difficult to understand. Consequently, many approaches to explaining opaque models have been proposed [18; 32]. Methods such as LIME [43] and SHAP [37] have been developed in order to provide post-hoc explanations by creating an approximate explanatory model of the opaque model. However, these methods provide no affordances for tuning the opaque model in response to an explanation.

2.2 Tunability

Research from interactive machine learning has shown the benefits of enabling users to tune learning models [4; 3; 46]. For example, Lou *et al.* [35] and Lou *et al.* [36] have demonstrated the value of GAMs and GA²Ms, which can be directly tuned by users via the alteration of shape functions. Likewise, Kulesza *et al.* [30] has shown the power of explanatory debugging of models. However, this research has focused on transparent, interpretable models, where the models can be tuned directly [54]. LIMEADE extends the paradigm of interactive machine learning and tuning to opaque models.

Recommender systems are a highly-studied domain for explainability and interactivity due to the feedback loop essential to the task of recommendation [2; 20; 33; 41; 48; 49; 50; 53; 55]. Some recommender systems enable the user to tune the system via affordances other than rating content [1; 7; 12; 13; 14; 17; 19; 24; 26; 28; 31; 38; 39; 45; 52]. Research has shown that explanations can improve a user's ability to accurately assess how much they will enjoy recommended content [11]. The combined affordances of actionability and explainability can lead to a higher degree of user satisfaction [22]; more trust in and perceived control of the system [16; 22; 40; 51]; and better mental models, without significantly increasing the cognitive load [29; 30; 44]. However, all of this work either relies on interpretable recommenders or interprets tunability in an algorithmic-specific fashion that is not extensible to an arbitrary opaque model. With our system Semantic Sanity, we demonstrate the benefits of LIMEADE's affordance for tuning an arbitrary opaque model.

2.3 Academic Paper Recommendation

For our experiments, we have chosen to study LIMEADE in the context of academic paper recommendation because the influx of papers published daily presents a significant challenge for researchers [10; 21; 25; 47]. Based on Beel *et al.* [8]'s survey of over 170 publications on academic paper recommendation only a few systems explain why papers have been recommended or respond to user feedback other than like/disliking specific papers, and all such systems rely on interpretable recommenders [7; 26; 14; 51; 39]. In addition, according to [8], of the publications with user evaluations, 58% report fewer than 15 participants, while we have 21.

3 Tuning Opaque Models with LIMEADE

With LIMEADE, we assume that the user would like to tune an opaque machine learning model. By *opaque*, we mean that the model architecture may be completely unknown, or (if known) it may have too many parameters and nonlinearities for a human to understand. However, we assume that the model's inputs and outputs are available, and that it can be retrained on new examples. We work in a semi-supervised learning setting, in which the goal is to learn a hypothesis that maps s-dimensional real-valued input vectors to binary output labels $\{-1,1\}$. We are given a set \mathcal{X}_L of labeled training examples (x,y,w), where $x\in\mathbb{R}^s$, y is the label to be learned, and w is the weight assigned to the example when training. Additionally, we optionally have a large, dense pool \mathcal{X}_U of unlabeled examples (x).

Our explainable machine learning problem setting closely follows that of previous work in explainable ML [43; 37]. First, we assume that each instance x can be represented as a binary-valued vector x' that lies in an *interpretable* space. For the example of paper recommendation, x is an opaque document embedding output by a large neural network, whereas x' is an interpretable vector of term occurrence statistics. In an image classification task, the dimensions of x might contain the raw RGB pixel values of the input image, whereas the dimensions of x' would correspond to larger, interpretable

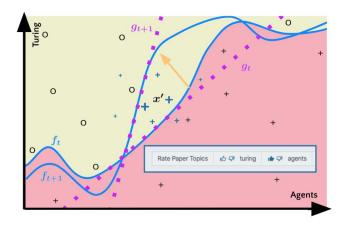


Figure 2: LIMEADE updates an arbitrary opaque ML model by creating pseudo-examples. Small black o's and +'s show the original training set, and shaded regions denote the complex boundary of the opaque classifier f_t . In order to explain a prediction, h(x'), the system generates a locally faithful explanatory model using LIME or an alternative method. This is g_t — shown as a purple dotted line. In practice, the explanatory model likely has many more than the two dimensions shown above, but suppose 'Turing' and 'agents' are highly weighted terms, hence used in the explanation. When the user specifies feature-level feedback, e.g., "I want more papers about 'agents", it could be used to directly alter a linear explanatory model (creating the new purple dotted line g_{t+1}); however, no simple update exists for an arbitrary, opaque classifier, which may be nonlinear and use completely different features, such as word embeddings. Instead, LIMEADE generates positive pseudo-examples (shown as blue +'s) that have the acted-upon feature and are similar to the predicted example. The pseudo-examples are weighted (shown by relative size) by their distance to the predicted example x' that was used to elicit feedback. By retraining on this augmented dataset, LIMEADE produces a tuned opaque classifier, shown as a changed nonlinear decision boundary f_{t+1} .

image components such as superpixels. LIMEADE assumes the existence of a function h'(x) = x' that maps the original representation (e.g. pixels) into the interpretable space (superpixels).

Given an instance x to explain, our approach uses an explanatory model g in the interpretable space that locally approximates f, i.e., $g(h'(z)) \approx f(z)$ for z' nearby x'. The model g can be any interpretable model, such as a decision tree or linear model, produced using LIME or a comparable method. We refer to the method that produces g as EXPLAIN(f,x,h'). In our experiments, we use a linear explanatory model, so $g(x') = w_0 + \sum_i w_i x_i'$, and the explanation surfaced for g(x') consists of high-impact terms in the model, i.e., those with high values for the product $w_i x_i'$.

Algorithm 1 details LIMEADE's approach to model tuning, and Figure 2 illustrates a concrete example of applying LIMEADE. Given an instance of interest, x, we obtain an explanation g(x') of the model's output f(x) using EXPLAIN(f,x,h'). The user can then provide a label on a feature of x'. Informally, a positive label on feature j of x' represents the user's assessment that examples x' near x' should tend to be positive when x'[j] = 1. For example, a

user of our paper recommendation system might give a positive label to the term "BERT" in a natural language processing paper to indicate interest in papers about the technique.

LIMEADE incorporates the user's action to improve the opaque model f by creating a set of k training pseudo-examples with repeated calls to GETINSTANCE (x,x',\mathcal{X}_U) . We experiment with two implementations of GETINSTANCE: sampling and generative. Sampling from the unlabeled pool is effective when the unlabeled pool is relatively dense, meaning one can acquire many examples with interpretable features similar to those of x'. Generative approaches can be helpful when data are less dense. For example, in image classification, LIMEADE could create synthetic pseudo-examples by greying out random subsets of the superpixels in the input image, essentially reversing LIME's process for generating the explanatory model, g.

LIMEADE only retains the pseudo-examples that contain the acted-upon feature j, i.e. those \tilde{x} for which $h'(\tilde{x})[j] = 1$. LIMEADE then assigns a label to each pseudo-example according to the user action: positive if the user assigned a positive feature label, and negative otherwise.

Algorithm 1 Tuning an opaque model using LIMEADE. Given a set of required inputs, LIMEADE solicits user tuning based on an explanation of a classified instance and retrains the opaque model accordingly. EXPLAIN is a function that generates an explanation for a given model and instance.

```
\mathcal{X}_L, \mathcal{X}_U // sets of labeled and unlabeled instances f_t: \mathbb{R}^s \to \{-1, 1\} // opaque classifier, version at time t x \in \mathbb{R}^s, x' \in \{0, 1\}^{s'} // instance & instance in interpret. rep.
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 $\begin{array}{ll} x \in \mathbb{R}^s, x' \in \{0,1\}^{s'} & \text{$//$} instance \& instance in interpret. rep.} \\ h': \mathbb{R}^s \to \{0,1\}^{s'} & \text{$//$} mapping s.t. } x' = h'(x) \\ \pi_{x'}: \{0,1\}^s \to \mathbb{R}_+ & \text{$//$} weighting based on distance } k \in \mathbb{N} & \text{$//$} number of pseudo-examples} \end{array}$

- 1: $g_t = \text{EXPLAIN}(f_t, x, h')$ // obtain explanatory model 2: // display key features of $g_t(x')$ to user, who then selects one
- feature (indexed j) as + or indicator of positive instance DISPLAY (g_t, x')
- 3: **receive** $a \in \{-1, 1\}$ **and** $j \in \{1, \dots, s'\}$

Inputs:

4: // select k instances, label them using action a, and weight according to distance from x'

```
\mathcal{N}_x \leftarrow \{\}
5: for 1, \dots, k do
6: \tilde{x} = \text{GETINSTANCE}(x, x', \mathcal{X}_U)
7: if h'(\tilde{x})[j] = 1 then
8: \mathcal{N}_x \leftarrow \mathcal{N}_x \cup \{(\tilde{x}, a, \pi_{x'}(h'(\tilde{x})))\}
9: end if
10: end for
11: \mathcal{X}_L \leftarrow \mathcal{X}_L \cup \mathcal{N}_x
12: f_{t+1} \leftarrow \text{RETRAIN}(\mathcal{X}_L, f_t)
13: return f_{t+1}
```

LIMEADE assigns each pseudo-example a weight based on its proximity to x', with examples more similar to x' given higher weight.² The reasons to weight local examples more highly are twofold: the explanatory method may only

²We measure proximity in the interpretable space, but it is equally possible to measure in the original space instead.

be locally correct [43], and the user actions may only be locally applicable. For example, the positive label on "BERT" discussed above is helpful within the local scope of natural language processing papers, but could become misleading if applied globally—in biology papers for example, the term "BERT" often refers to a different meaning (the "BERT gene"). After selecting and weighting the pseudo-examples, LIMEADE can optionally condense the selections (e.g., collapsing the examples into a single centroid for efficiency, as we do in our experiments). Finally, LIMEADE adds the resulting pseudo-examples to the labeled training set \mathcal{X}_L and calls RETRAIN to train the classifier f on the new data set.

To summarize, LIMEADE is a general approach for tuning an opaque model that is applicable to an interactive machine learning task whenever the following requirements are met:

- A base (opaque) model. The only models not compatible with LIMEADE are truly blackbox models, where the user has no access to the training data or the ability to retrain.
- A transparent explanatory model (such as one produced by LIME).
- 3. The ability to sample or generate instances with featurizations in both the base and explanatory models.
- The ability to receive feedback on an explanatory model feature, indicating whether it is a positive or negative indicator of the instance label.
- 5. A distance metric between instances.
- 6. The ability to detect for a given instance the presence or absence of each explanatory model feature that received feedback in Step 4.

4 Semantic Sanity: Using LIMEADE to Recommend Papers

To test LIMEADE, we wanted human users who were authentically motivated to understand and improve an ML classifier. Much prior research in explainable AI has relied on Mechanical Turk workers, who are instructed to 'care' about the quality of explanations, but whose motivations are typically unverified. Instead, we built Semantic Sanity, a computer science (CS) research-paper recommender system based on Andrej Karpathy's arXiv Sanity Preserver [27]. Deployed as a publicly-available platform, Semantic Sanity enables users to curate feeds from over 150,000 CS papers recently published on arXiv.org. With this testbed, users are implicitly incentivized to understand and improve the ML model that powers their feed in order to receive more interesting papers. Note further that each user is a task expert, since they determine their own preferences.

4.1 Neural Recommender

To generate individual recommendations, we utilize a neural model consisting of a linear SVM on top of neural paper embeddings pre-trained on a similar papers task. Each paper is represented by the first vector (i.e., the [CLS] token typically chosen for text classification) after encoding the paper title and abstract using SciBERT [9]. The neural embedding model is finetuned on a triplet loss $\mathcal{L} = max(0, v_i^T v_+ - v_+)$

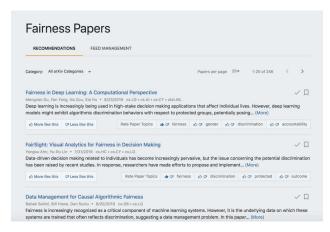


Figure 3: The UI for a feed in Semantic Sanity. Under each paper, the system presents four terms to explain why it was recommended and solicits feedback with "Rate Paper Topics": by clicking thumbs up or down, the user can request that the feed include more or less of the specified topic.

 $v_i^Tv_-+m)$ where m is a margin hyperparameter and $v_i,\,v_+$ and v_- are the vectors representing a query paper, a similar paper to the query paper, and a dissimilar paper to the query paper, respectively. The similar paper triples are heuristically defined using citations, from the SEMANTIC SCHOLAR corpus [6] treating cited papers as more similar than un-cited papers. Recommendations are generated by training the model on a user's annotation history, with additional negative examples randomly drawn from the full corpus of unannotated papers.

A user begins the process of curating their feed by either selecting a specific arXiv CS category or issuing a keyword search and then rating a handful of the resulting papers. A feed consists of a list of recommended papers sorted by predicted recommendation score (see Figure 3). Each paper can be rated using traditional "More like this" or "Less like this" buttons underneath each paper description.

4.2 Implementation of Explanations and Feedback

Our UI for Semantic Sanity uses LIMEADE to display four terms from the paper text along with each recommended paper, which serve as the explanation for why the paper was recommended. To the left of each term in the explanation are thumbs-up and thumbs-down buttons, enabling the user to *act* on the explanation and indicate if they would like to see more or fewer papers related to that term.

For our EXPLAIN function, we train a simple, linear explanatory model using uni- and bigram features.³ We discuss how LIMEADE chooses which terms to display as the explanation in Section 4.3. Furthermore, next to each explanatory term are thumbs up and down buttons (see Figure 3). When the user provides feedback with these buttons, LIMEADE generates pseudo-examples and retrains the neural model as

³Specifically, we select the 20,000 features with the highest term frequency across our corpus. Note that our approach of using a posthoc explanatory model is similar to that used by LIME, except our explanatory model is trained as a global, rather than local, approximation of the neural model [43].

explained in Section 3. We use a generative approach within GETINSTANCE that leverages the unlabeled pool of papers. We select the top 100 papers from the full corpus with the highest TF-IDF value for the feedback term, and generate a single synthetic pseudoexample (i.e., we use k=1) equal to the centroid of these papers' embeddings. The example is appended to the user's history and labeled with the user's annotation of the term (+/-).

4.3 Generating Diverse Explanations

Given the explanatory model, LIMEADE's DISPLAY function chooses explanations to display by computing each term's contribution to the output of the linear model for the given paper, which is equal to the product of the term's TF-IDF value for the paper with the term's feature weight in the linear model. The canonical explanation choice is to surface the terms with the highest-magnitude contributions in the linear model [43]; we call this a greedy approach. However, comments from early users of our paper recommender indicated that there is a tradeoff between using the greedy approach and providing affordances for feedback. In particular, user action on a feature will lead the model to place increasing importance on it and correlated features. With the greedy approach, these terms will begin to dominate the explanations, which limits opportunities for feedback. On the other hand, a diversity-biased strategy would present more unique terms to provide more opportunities for feedback, but would consequently diverge from using the terms with the highest contributions to the explanatory model.

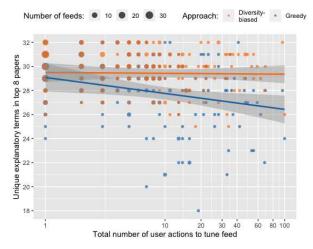


Figure 4: A scatter plot showing the number of unique explanation terms in the first page of the feed vs. the number of actions taken by the user to tune their feed. The orange dots correspond to the diversity-biased explanations currently used in the system. The blue dots correspond to greedy explanations, where the most important terms are surfaced, without stochasticity. Note that greedy explanations display a stronger negative correlation between unique terms and term annotations than diversity-biased explanations.

Based on this feedback, our final implementation of DISPLAY uses a diversity-biased approach that samples explanatory features controlled by a parameter $\gamma=4$. Specifically,

we sample terms proportionally to the magnitude of term contribution, raised to the γ power (higher values of γ result in a more greedy approach, whereas lower values increase diversity). To further reduce term redundancy in each recommended paper's explanation, we used the Python NLTK PorterStemmer [34] to deduplicate terms with the same stems (e.g., "fair" and "fairness") from each explanation.

To help illustrate the impact of the explanation-action tradeoff, and the distinction between our diversity-biased approach and the canonical greedy method, we perform an analysis on the logs of 300 users' feeds from the online deployment of Semantic Sanity. For each user, we compute (i) the total number of actions the user has taken on displayed explanatory terms, and (ii) the number of unique explanation terms among the latest top eight recommended papers under our diversity-biased DISPLAY implementation. We then repeat (ii) but with DISPLAY with $\gamma = \infty$ to simulate what explanatory terms the users would see today if we were to switch to a greedy approach.

In accordance with the explanation-action tradeoff, we observe in Figure 4 that the number of unique explanation terms (i.e. tuning affordances) tends to be lower under a greedy approach. Furthermore, this effect grows stronger as users tune their feeds to be increasingly specific to a particular topic.⁴ In contrast, the number of affordances remains relatively constant under our diversity-biased approach. This comes at the expense of having some explanation terms with lower contribution weight within the explanatory model.

5 Evaluation: User Study

In order to evaluate the effectiveness of our LIMEADE-based system for recommending papers, we performed an in-person user study.

5.1 Experimental Setup

We recruited 21 participants through the University of Washington's computer science email lists. All participants were adults who reported experience with reading computer science research papers in our screening questionnaire. Each session lasted one hour, and each participant was compensated with a \$25 gift card.

Subjects were asked to curate feeds of computer science papers pertaining to a topic of their choice using two different recommendation user interfaces (UIs), one that used LIMEADE to provide tunable explanations, and one that did not present explanations (the baseline); other than this difference, the UIs were the same. Subjects were asked to choose a topic that they were interested in following over time as new papers are added to the arXiv, but not so general that it is already covered by an existing arXiv CS category (e.g., artificial intelligence). Once a topic was selected, each participant

⁴We note that Figure 4 likely understates the impact of the tradeoff because users had been exposed to explanations under the diversity-biased approach prior to this analysis. Had they been exposed to explanations under the greedy approach for the entirety of their feed-tuning process, we likely would observe an even stronger crowding-out effect on the explanatory terms.

was asked to name the desired feed, which served as the goal for curation using both UIs.

Each participant began curation as described in Section 4.1, selecting exactly three seed papers that were then used to initialize the feeds in both UIs. Both systems surfaced the same initial recommendations and thus had identical initial states for each participant. Each participant was then presented with one of the two UIs and given instructions on how to use it. 11 participants received the baseline system first, and 10 received the LIMEADE system first. They were then presented with the second UI. For both UIs, the participants were told to use as many or as few annotations as desired until their feed was curated to their liking, or a maximum of 10 minutes was reached. We recorded the participants' annotations for both feeds. They were then asked to rate a blind list of combined recommendations from the two feeds that they had curated, according to whether they would like to see each paper in their desired feed. These recommendations were generated on a held-out paper corpus, disjoint from the papers available within the feed UIs.

5.2 Quantitative results

Data was successfully collected for all 21 participants. The participants' chosen topics varied greatly, including "Spiking Neural Networks," "Moderation of Online Communities," and "Dialogue System Evaluation."

We asked each participant to provide overall ratings for each system, and to state which system they preferred along dimensions such as trust and intuitiveness. The results are summarized in Tables 1 and 2.⁵

Which system	Baseline	Ours	p-value
trust more?	4	17	0.043
more control?	0	21	$pprox\!0$
more transparent?	3	18	0.012
more intuitive?	12	9	0.664
not missing relevant papers?	3	18	0.012

Table 1: Among 21 participants, most prefer our system over the baseline when prompted these questions. Boldface indicates a statistically significant result under a two-sided Binomial test against a null hypothesis of no preference.

Likert scale rating	Baseline	Ours	p-value
Overall system Would use again?	3.38 ± 0.59 3.38 ± 1.16	3.85 ± 0.57 3.90 ± 0.94	0.043 0.257

Table 2: Mean \pm Standard Deviation of 21 participant ratings of each system. Ratings were on a scale from 1 (worst/no) to 5 (best/yes). Boldface indicates a statistically significant result under a two-sided paired t-test against a null hypothesis of zero mean difference between the systems.

Overall, participants rated our approach significantly higher than the baseline. They also rated it significantly higher on trust, control, and transparency, and in confidence that their recommendations were not missing relevant papers. Understandably, our system appeared less intuitive to participants than the baseline due to the increased complexity of the UI, though this result was not statistically significant. Finally, while not statistically significant due to small sample size, participants indicated more likelihood to use our system again over the baseline.

We also investigated whether the feature-level feedback provided by LIMEADE measurably increased the quality of participants' feed. To do this we showed participants the top 20 recommendations generated by both systems on the heldout corpus of papers and measured their ratings of the results. Specifically, we computed the discounted cumulative gain (DCG)⁶ and average precision (AP), common metrics for assessing recommendation feed quality. For DCG, we observe a mean difference of 0.259 in favor of the baseline system recommendations; however, the corrected p-value for the two-sided, paired t-test for mean differences is 0.218, indicating no significant difference in feed quality between the baseline system and the tunable system with LIMEADE under DCG. For AP, we observe a mean difference of 0.0412 in favor of the baseline system, with a corrected p-value of 0.257, also indicating lack of significant difference in quality with respect to AP.

5.3 Qualitative feedback

We analyze participants' free text responses and provide a sample of quotes that complement the quantiative results. Overall, participants found the tuning affordance granted by our system helpful:

"The explanations here were especially useful in their capacity as decisions rather than just explanations. I would have found them really really annoying if they were presented only as an explanation of why you thought I would like a paper, rather than an attribute I could ask for more or less of."

In particular, participants stressed the importance of actionable explanations as a filtering mechanism:

"The topics feature was excellent, because there are many papers which cover *some* topics I like but also some that I don't, and this let me pick that out."

Some participants indicated a preference for an even more diversity-biased system:

"After a few minutes, almost all the same terms that I had liked were coming up, so there were few new terms for me to thumbs up or down. I think if the system could focus on bringing up relevant papers that have a new term or two to which I can react, that would make the curation even better."

⁵For all statistical significance tests, we report adjusted *p*-values using the Holm-Bonferroni procedure for multiple comparisons [23] implemented in the P.ADJUST library in R [42].

⁶We did not use normalized discounted cumulative gain (NDCG) because the participants liked different numbers of papers.

6 Conclusion & Future Work

To our knowledge, LIMEADE is the first general framework for tuning an arbitrary opaque learning model based on feedback corresponding to an approximate explanation. Using our implementation of LIMEADE for Semantic Sanity, a publicly-available computer science research paper recommender, we conducted a user study and showed that participants strongly prefer our tunable system over the baseline according to metrics such as trust, perceived control, and overall satisfaction.

In future work, we intend to experiment with LIMEADE on other domains, such as image data, in order to further evaluate the effectiveness of our method.

There are also interesting questions about the interplay between the perceived quality of an approximate explanation and the ability (or inability) to tune such a model — does LIMEADE cause users to better trust explanations, such as those produced by LIME?

Finally, as more online users adopt our recommender tool, it will become increasingly important to experiment with aspects of LIMEADE that benefit from personalization. For example, we could grant users more control over the explanation diversity parameter γ and the relative strength of each tuning adjustment upon retraining.

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