How do Humans Understand Explanations from Machine Learning Systems?  
An Evaluation of the Human-Interpretability of Explanation

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Abstract

Recent years have seen a boom in interest in machine learning systems that can provide a human-understandable rationale for their predictions or decisions. However, exactly what kinds of explanation are truly human-interpretable remains poorly understood. This work advances our understanding of what makes explanations interpretable in the specific context of verification. Suppose we have a machine learning system that predicts X, and we provide rationale for this prediction X. Given an input, an explanation, and an output, is the output consistent with the input and the supposed rationale? Via a series of user-studies, we identify what kinds of increases in complexity have the greatest effect on the time it takes for humans to verify the rationale, and which seem relatively insensitive.

1 Introduction

Interpretable machine learning systems provide not only decisions or predictions but also explanation for their outputs. Explanations can help increase trust and safety by identifying when the recommendation is reasonable when it is not. While interpretability has a long history in AI [Michie 1988], the relatively recent widespread adoption of machine learning systems in real, complex environments has lead to an increased attention to interpretable machine learning systems, with applications including understanding notifications on mobile devices [Mehrotra et al. 2017, Wang et al. 2016], calculating stroke risk [Letham et al. 2015], and designing materials [Raccuglia et al. 2016]. Techniques for ascertaining the provenance of a prediction are also popular within the
machine learning community as ways for us to simply understand our increasingly complex models [Lei et al., 2016, Selvaraju et al., 2016, Adler et al., 2016].

The increased interest in interpretability has resulted in many forms of explanation being proposed, ranging from classical approaches such as decision trees [Breiman et al., 1984] to input gradients or other forms of (possibly smoothed) sensitivity analysis [Selvaraju et al., 2016, Ribeiro et al. 2016, Lei et al. 2016], generalized additive models [Caruana et al., 2015], procedures [Singh et al., 2016], falling rule lists [Wang and Rudin, 2015], exemplars [Kim et al., 2014, Frey and Dueck, 2007] and decision sets [Lakkaraju et al., 2016]—to name a few. In all of these cases, there is a face-validity to the proposed form of explanation: if the explanation was not human-interpretable, clearly it would not have passed peer review.

That said, these works provide little guidance about when different kinds of explanation might be appropriate, and within a class of explanations—such as decision-trees or decision-sets—what are the limitations of human reasoning. For example, it is hard to imagine that a human would find a 5000-node decision tree as interpretable as 5-node decision tree, for any reasonable notion of interpretable. The reason the explanation is desired is also often left implicit. In [Doshi-Velez and Kim, 2017], we point to a growing need for the interpretable machine learning community to engage with the human factors and cognitive science of interpretability: we can spend enormous efforts optimizing all kinds of models and regularizers, but that effort is only worthwhile if those models and regularizers actually solve the original human-centered task of providing explanation. Carefully controlled human-subject experiments provide an evidence-based approach to identify what kinds of regularizers we should be using.

In this work, we make modest but concrete strides toward this large goal of quantifying what makes explanation human-interpretable. We shall assume that there exists some explanation system that generates the explanation—for example, there exist a variety of approaches that use perturbations around a point of interest to produce a local decision boundary [Ribeiro et al., 2016, Singh et al., 2016]. Our question is: What kinds of explanation can humans most easily utilize? Below, we describe the kind of task we shall explore, as well as the form of the explanation.

Choice of Task  The question of what kinds of explanation a human can utilize implies the presence of a downstream task. The task may be intrinsic—relying on just the explanation alone—or extrinsic—relying on the explanation and other facts about the environment. Intrinsic tasks include problems such as verification—given an input, output, and explanation, can the human user verify that the output is consistent with the input and provided explanation?—and counterfactual reasoning—given an input, output, and explanation, can the human subject identify what input changes would result in a different output? In contrast, extrinsic tasks include goals such as safety—given the input, output, explanation, and observations of the world, does the explanation help the human user identify when the agent is going to make a mistake?—and trust—given the input, output, explanation, and observations of the world, does the explanation increase the human user’s confidence in the agent? Evaluation on extrinsic tasks, while ultimately what we care about, require careful experimental design that ensures all subjects have similar knowledge and assumptions about
the environment. One must also tease apart confusions between human perception of knowledge with actual knowledge: for example, it may be possible to manipulate trust arbitrarily separately from prediction accuracy. Thus, evaluating extrinsic tasks is more challenging than intrinsic ones.

In this work, we will focus on the simplest intrinsic setting: verification. Given a specific input, explanation, and output, can we quickly determine whether the output is consistent with the input and explanation? Such a setting may arise in consumer recommendation scenarios—for example, a salesperson may wish to ensure that a specific product recommendation is consistent with a consumer’s preferences. Starting simple also provides an opportunity to explore aspects relevant to the experimental design.

**Choice of Explanation Form**  As mentioned above, there have been many forms of explanation proposed, ranging from decision trees to gradients of neural networks. In this work, we consider explanations that are in the form of decision sets. Decision sets are a particular form of procedure consisting of a collection of cases, each mapping some function of the inputs to a collection of outputs. An example of a decision set is given below

Figure 1: Example of a decision set explanation.

where each line contains a clause in disjunctive normal form (an or-of-ands) of the inputs, which, if true, provides a way to verify the output (also in disjunctive normal form). As argued in [Lakkaraju et al.][2016], decision sets are relatively easy for humans to parse given a specific instance, because they can scan for the rule that applies and choose the accompanying output. Decision sets (also known as rule sets) also enjoy a long history of optimization techniques, ranging from [Frank and Witten][1998], [Cohen][1995], [Clark and Boswell][1991] to [Lakkaraju et al.][2016].

However, we can also already see that there are many factors that could potentially make the decision set more or less challenging to follow: in addition to the number of lines, there are ways in which terms interact in the disjunctions and conjunctions, and, more subtly, aspects such as how often terms appear and whether terms represent intermediate concepts. Which of these factors are most relevant when it comes to a human’s ability to process and utilize an explanation, and to what extent? The answer to this question has important implications for the design of explanation systems in interpretable machine learning, especially if we find that our explanation-processing ability is relatively robust to variation in some factors but not others.

**Contributions** The core contribution of this work is to provide an empirical grounding for what kinds of explanations humans can utilize. We find that while almost all increases in the complexity of an explanation result in longer response times, some types of complexity—such as the number of lines, or the number of new concepts introduced—have a much bigger effect than others—such as variable repetition. We also find some unintuitive patterns, such as how participants seem to prefer
an explanation that requires a single, more complex line to one that spans multiple simpler lines (each defining a new concept for the next line). While more work is clearly needed in this area, we take initial steps in identifying what kinds of factors are most important to optimize for when providing explanation to humans.

2 Related Work

Interpretable machine learning methods aim to optimize models for both succinct explanation and predictive performance. Common types of explanation include regressions with simple, human-simulatable functions [Caruana et al., 2015, Kim et al., 2015a, Rüping 2006, Bucilu et al., 2006, Ustun and Rudin, 2016, Doshi-Velez et al., 2015, Kim et al., 2015b, Krakovna and Doshi-Velez, 2016, Hughes et al., 2016, Jung et al., 2017], various kinds of logic-based methods [Wang and Rudin, 2015, Lakkaraju et al., 2016, Singh et al., 2016, Liu and Tsang, 2016, Safavian and Landgrebe, 1991, Wang et al., 2017], techniques for extracting local explanations from black-box models [Ribeiro et al., 2016, Lei et al., 2016, Adler et al., 2016, Selvaraju et al., 2016, Smilkov et al., 2017, Shrikumar et al., 2016, Kindermans et al., 2017, Ross et al., 2017], and visualization [Wattenberg et al., 2016]. There exist a range of technical approaches to derive each form of explanation, whether it be learning sparse models [Mehmood et al., 2012, Chandrashekar and Sahin, 2014], monotone functions [Canini et al., 2016], or efficient logic-based models [Rivest, 1987]. Related to our work, there also exists a history of identify human-relevant concepts from data, including disentangled representations [Chen et al., 2016] and predicate invention in inductive logic programming [Muggleton et al., 2015]. While the algorithms are sophisticated, the measures of interpretability are often not—it is common for researchers to simply appeal to the face-validity of the results that they find (i.e., “this result makes sense to the human reader”) [Caruana et al., 2015, Lei et al., 2016, Ribeiro et al., 2016].

In parallel, the literature on explanation in psychology also offers several general insights into the design of interpretable AI systems. For example, humans prefer explanations that are both simple and highly probable [Lombrozo 2007]. Human explanations typically appeal to causal structure [Lombrozo 2006] and counterfactuals [Keil 2006]. Miller [1956] famously argued that humans can hold about seven items simultaneously in working memory, suggesting that human-interpretable explanations should obey some kind of capacity limit (importantly, these items can correspond to complex cognitive chunks—for example, ‘CIAFBINSA’ is easier to remember when it is chunked as ‘CIA’, ‘FBI’, ‘NSA.’). Orthogonally, Kahneman [2011] notes that humans have different modes of thinking, and larger explanations might push humans into a more careful, rational thinking mode. Machine learning researchers can convert these concepts into notions such as sparsity or simulatability, but the work to determine answers to questions such as “how sparse?” or “how long?” requires empirical evaluation.

Existing studies evaluating the human-interpretability of explanation often fall into the A-B test framework, in which a proposed model is being compared to some competitor, generally on an intrinsic task. For example, Kim et al. [2014] showed that human subjects’ performance on a classification task was better when using examples as representation than when using non-example-based representation. Lakkaraju et al. [2016] performed a user study in which they found subjects are faster and more accurate at describing local decision boundaries based on decision sets rather
than rule lists. Subramanian et al. [1992] found that users prefer decision trees to tables in games, whereas Huysmans et al. [2011] found users prefer, and are more accurate, with decision tables rather than other classifiers in a credit scoring domain. Hayete and Bienkowska [2004] found a preference for non-oblique splits in decision trees (see Freitas [2014] for more detailed survey). These works provide quantitative evaluations of the human-interpretability of explanation, but rarely identify what properties are most essential for what contexts—which is critical for generalization.

Specific application areas have also evaluated the desired properties of an explanation within the context of the application. For example, Tintarev and Masthoff [2015] provides a survey in the context of recommendation systems, noting differences between the kind of explanations that manipulate trust [Cosley et al., 2003] and the kind that increase the odds of a good decision [Bilgic and Mooney, 2005]. In many cases, these studies are looking at whether the explanation has an effect, sometimes also considering a few different kinds of explanation (actions of similar customers, etc.). Horsky et al. [2012] describe how presenting the right clinical data alongside a decision support recommendation can help with adoption and trust. Bussone et al. [2015] found that overly detailed explanations from clinical decision support systems enhance trust but also create over-reliance; short or absent explanations prevent over-reliance but decrease trust. These studies span a variety of extrinsic tasks, and again given the specificity of each explanation type, identifying generalizable properties is challenging.

Closer to the objectives of the proposed work, Kulesza et al. [2013] performed a qualitative study in which they varied the soundness (nothing but the truth) and the completeness (the whole truth) of an explanation in a recommendation system setting. They found completeness was important for participants to build accurate mental models of the system. Allahyari and Lavesson [2011], Elomaa [2017] also find that larger models can sometimes be more interpretable. Schmid et al. [2016] find that human-recognizable intermediate predicates in inductive knowledge programs can sometimes improve simulation time. Poursabzi-Sangdeh et al. [2017] manipulate the size and transparency of an explanation and find that longer explanations and black-box models are harder to simulate accurately (even given many instances) on a real-world application predicting housing prices. Our work fits into this category of empirical study of explanation evaluation; we perform controlled studies on a pair of synthetic application to assess the effect of a large set of explanation parameters.

3 Methods

Our main research question is to determine what properties of decision sets are most relevant for human users to be able to utilize the explanations for verification. In order to carefully control various properties of the explanation and the context, in the following we shall present human subjects with explanations that could have been machine-generated, but were in fact generated by us. Before describing our experiment, we emphasize that while our explanations are not actually machine-generated, our findings provide suggestions to designers of interpretable machine learning systems about what parameters affect the usability of an explanation, and which should be optimized when producing explanations.
3.1 Factors Varied

Even within decision sets, there are a large number of ways in which the explanations could be varied. Following initial pilot studies (see Appendix), we chose to focus on the three main kinds of variation (described below). We also tested on two different domains—a faux recipe recommendation domain and a faux clinical decision support domain—to see if the context would result in different explanation processing while other factors were held constant.

Explanation Variation  We explored the following sources of explanation variation:

• **V1: Explanation Size.** We varied the size of the explanation across two dimensions: the total number of lines in the decision set, and the maximum number of terms within the output clause. The first corresponds to increasing the vertical size of the explanation—the number of cases—while the second corresponds to increasing the horizontal size of the explanation—the complexity of each case. We focused on output clauses because they were harder to parse: input clauses could be quickly scanned for setting-related terms, but output clauses had to be read through and processed completely to verify an explanation. We hypothesized that increasing the size of the explanation across either dimension would increase the time required to perform the verification task.

• **V2: Creating New Types of Cognitive Chunks.** In Figure 2, the first line of the decision set introduces a new cognitive chunk: if the alien is ‘checking the news’ or ‘coughing,’ that corresponds to a new concept ‘windy.’ On one hand, creating new cognitive chunks can make an explanation more succinct. On the other hand, the human must now process an additional idea. We varied two aspects related to new cognitive chunks. First, we simply adjusted the number of new cognitive chunks present in the explanation. All of the cognitive chunks were necessary for verification, to ensure that the participant had to traverse all of concepts instead of skimming for the relevant one. Second, we tested whether it was more helpful to introduce a new cognitive chunk or leave it implicit: for example, instead of introducing a concept ‘windy’ for ‘checking the news or coughing,’ (explicit) we could simply include ‘checking the news or coughing’ wherever windy appeared (implicit). We hypothesized that adding cognitive chunks would increase the time required to process an explanation, because the user would have to consider more lines in the decision list to come to a conclusion. However, we hypothesized that it would still be more time-efficient to introduce the new chunk rather than having long clauses that implicitly contained the meaning of the chunk.

• **V3: Repeated Terms in an Explanation.** Another factor that might affect humans’ ability to process an explanation is how often terms are used. For example, if input conditions in the decision list have little overlap, then it may be faster to find the appropriate one because there are fewer relevant cases to consider. We hypothesized that if an input condition appeared in several lines of the explanation, this would increase the time it took to search for the correct

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2One can imagine this being akin to giving names to nodes in a complex model, such as a neural network.
rule in the explanation. (Repeated terms was also a factor used by [Lakkaraju et al., 2016] to measure interpretability.)

Domain Variation  Below we describe the two contexts, or domains, that we used in our experiments: recipe recommendations (familiar) and clinical decision support (unfamiliar). The domains were designed to feel very different but such that the verification tasks could be made to exactly parallel each other, allowing us to investigate the effect of the domain context in situations when the form of the explanation was exactly the same. We hypothesized that these trends would be consistent in both the recipe and clinical domains.

Alien Recipes. In the first domain, study participants were told that the machine learning system had studied a group of aliens and determined each of their individual food preferences in various settings (e.g., snowing, weekend). Each task involved presenting participants with the setting (the input), the system’s description of the current alien’s preferences (the explanation), and a set of recommended ingredients (the output). The user was then asked whether the ingredients recommendation was a good one. This scenario represents a setting in which customers may wish to know why a certain product or products were recommended to them. Aliens were introduced in order to avoid the subject’s prior knowledge or preferences about settings and food affecting their responses; each task involved a different alien so that each explanation could be unique. All non-literals (e.g., what ingredients were spices) were defined in a dictionary so that all participants would have the same cognitive chunks.

Alien Medicine. In the second domain, study participants were told that the machine learning system had studied a group of aliens and determined personalized treatment strategies for various symptoms (e.g., sore throat). Each task involved presenting participants with the symptoms (the input), the system’s description of the alien’s personalized treatment strategy (the explanation), and a set of recommended drugs (the output). The user was then asked whether the drugs recommended were appropriate. This scenario closely matches a clinical decision support setting in which a system might suggest a treatment given a patient’s symptoms, and the clinician may wish to know why the system chose a particular treatment.

As before, aliens were chosen to avoid the subject’s prior medical knowledge from affecting their responses; each task involved personalized medicine so that each explanation could be unique. We chose drug names that corresponded with the first letter of the illness (e.g., antibiotic medications were Aerove, Adenon and Athoxin) so as to replicate the level of ease and familiarity of food names. Again, all drug names and categories were provided in a dictionary so that participants would have the same cognitive chunks.

In our experiments, we maintained an exact correspondence between inputs (setting vs. symptoms), outputs (foods vs. drugs), categories (food categories vs. drug categories), and the forms of the explanation. These parallels allowed us to test whether changing the domain from a relatively familiar, low-risk product recommendation setting to a relatively unfamiliar, higher-risk decision-making setting affected how subjects utilized the explanations for verification.
3.2 Experimental Design and Interface

The three kinds of variation and two domains resulted in six total experiments. In the recipe domain, we held the list of ingredients, food categories, and possible input conditions constant. Similarly, in the clinical domain, we held the list of symptoms, medicine categories, and possible input conditions constant. The levels were as follows:

- **Length of the explanation (V1).** We manipulated the length of the explanation (varying between 2, 6, and 10 lines) and the length of the output clause (varying between 2 and 5 terms). Each combination was tested twice within an experiment, for a total of 12 questions.

- **Introducing new concepts (V2):** We manipulated the number of cognitive chunks introduced (varying from 1 to 5), and whether they were embedded into the explanation or abstracted out into new cognitive chunks. Each combination was tested once within an experiment, for a total of 10 questions.

- **Repeated terms (V3):** We manipulated the number of times the input conditions appeared in the explanation (varying from 1 to 5) and held the number of lines and length of clauses constant. Each combination was tested twice within an experiment, for a total of 10 questions.

The outputs were consistent with the explanation and the input 50% of the time, so subjects could not simply learn that the outputs were always (in)consistent.

Participants were recruited via Amazon Mechanical Turk. Before starting the experiment, they were given a tutorial on the verification task and the interface. Then they were given a set of three practice questions. Following the practice questions, they started the core questions for each experiment. They were told that their primary goal was accuracy, and their secondary goal was speed. While the questions were the same for all participants, the order of the questions was randomized for every participant. Each participant only participated in one of the experiments. For example, one participant might have completed a 12-question experiment on the effect of varying explanation length in the recipe domain, while another would have completed a 10-question experiment on the effect of repeated terms in the clinical domain. Experiments were kept short to avoid subjects getting tired.

**Metrics**  We recorded three metrics: response time, accuracy, and subjective satisfaction. Response time was measured as the number of seconds from when the task was displayed until the subject hit the submit button on the interface. Accuracy was measured if the subject correctly identified whether the output was consistent with the input and the explanation (a radio button). After each submitting their answer for each question, the participant was also asked to subjectively rate the quality of the explanation on a scale from one to ten.
Figure 2: Screenshots of our interface for a task. In the Recipe Domain, the supposed machine learning system has recommended the ingredients in the lower left box, based on its observations of the alien (center box). The top box shows the system’s explanation. In this case, the recommended ingredients are consistent with the explanation and the inputs: The input conditions are weekend and windy (implied by coughing), and the recommendation of fruit and grains follows from the last line of the explanation. In the Clinical Domain, the supposed machine learning system has recommended the medication in the lower box, based on its observations of the alien’s symptoms (center box). The top box shows the system’s reasoning. The interface has exactly the same form as the recipe domain.
Table 1: Participant Demographics. There were no patients over 69 years old. 4.2% of participants reported “other” for their education level. The rates of participants from Australia, Europe, Latin America, and South America were all less than 0.5%. (All participants were included in the analyses, but we do not list specific proportions for them for brevity.)

| Feature   | Category : Proportion |
|-----------|-----------------------|
| Age       | 18-34 : 59.0%         |
|           | 35-50 : 35.1%         |
|           | 51-69 : 5.9%          |
| Education | High School : 28.5%   |
|           | Bachelor’s : 52.4%    |
|           | Beyond Bachelor’s: 14.9%|
| Gender    | Male : 58.8%          |
|           | Female : 41.2%        |
| Region    | US/Canada : 87.1%     |
|           | Asia : 11.4%          |

**Experimental Interface**  Figure 2 shows our interfaces for the Recipe and Clinical domains. The **observations** section (middle) refers to the inputs into the algorithm. The **recommendation** section refers to the output of the algorithm. The **preferences** section (top) contains the explanation—the reasoning that the supposed machine learning system used to suggest the output (i.e., recommendation) given the input, presented as a procedure in the form of a decision set. Finally, the **ingredients** section in the Recipe domain (and the **disease medications** section in the Clinical domain) contained a dictionary of **cognitive chunks** relevant to the experiment (for example, the fact that bagels, rice, and pasta are all grains). Including this list explicitly allowed us to control for the fact that some human subjects may be more familiar with various concepts than others.

The choice of location for these elements was chosen based on pilot studies—while an ordering of input, explanation, output might make more sense for an AI expert, we found that presenting the information in the format of Figure 2 seemed to be easier for subjects to follow in our preliminary explorations. We also found that presenting the decision set as a decision set seemed easier to follow than converting it into paragraphs. Finally, we colored the input conditions in blue and outputs in orange within the explanation. We found that this highlighting system made it easier for participants to parse the explanations for input conditions.

## 4 Results

We recruited 100 subjects for each of our six experiments, for a total of 600 subjects all together. Table 1 summarizes the demographics of our subjects across the experiments. Most participants were from the US or Canada (with the remainder being almost exclusively from Asia) and were less than 50 years old. A majority had a Bachelor’s degree. There were somewhat more male participants than female. We note that US and Canadian participants with moderate to high education dominate this survey, and results may be different for people from different cultures and backgrounds.

All participants completed the full task (each survey was only 10-12 questions). In the analysis below, however, we exclude participants who did not get all three initial practice questions or all two of the additional practice questions correct. While this may have the effect of artificially increasing the accuracy rates overall—we are only including participants who could already perform the task to a reasonable extent—this criterion helped filter the substantial proportion of participants who
Table 2: Number of participants who met our inclusion criteria for each experiment.

|                        | Recipe Domain | Clinical Domain |
|------------------------|---------------|-----------------|
| Explanation Size       | N=88          | N=73            |
| New Cognitive Chunks   | N=77          | N=73            |
| Variable Repetition    | N=70          | N=71            |

Figure 3: Accuracy across the six experiments. Vertical lines indicate standard errors.

were simply breezing through the experiment to get their payment. We also excluded one participant in the clinical version of the cognitive chunks experiment who did get sufficient practice questions correct but then took more than ten minutes to answer a single question. Table 2 describes the total number of participants that remained in each experiment out of the original 100 participants.

Figures 3 and 4 present the accuracy and response time across all six experiments, respectively. Response time is shown for subjects who correctly answered the questions. Figure 5 shows the trends in the participants’ subjective evaluation—whether they thought the explanation was easy to follow or not. We evaluated the statistical significance of the trends in these figures using a linear regression for the continuous outputs (response time, subjective score) and a logistic regression for binary outputs (accuracy). For each outcome, one regression was performed for each of the experiments V1, V2, and V3. If an experiment had more than one independent variable—e.g. number of lines and terms in output—we performed one regression with both variables. Regressions were performed with the statsmodels library [Seabold and Perktold 2010] and included an intercept term. Table 3 summarizes these results.
Table 3: Significance tests for each factor. Linear and logistic regression weights were computed for continuous and binary outputs respectively (the subjective evaluations were treated as continuous). A single regression was computed for each of V1, V2, and V3. Highlighted p-values are significant at $\alpha = 0.05$ with a Bonferroni multiple comparisons correction across all tests of all experiments.

| Factor                                      | Recipe weight | p-value | Clinical weight | p-value |
|---------------------------------------------|---------------|---------|-----------------|---------|
| Explanation Length (V1)                     | -0.0116       | 0.00367 | -0.0171         | 0.000127 |
| Number of Output Terms (V1)                 | -0.0161       | 0.0629  | 0.00685         | 0.48    |
| Number of Cognitive Chunks (V2)             | 0.0221        | 0.0377  | 0.0427          | 0.00044 |
| Implicit Cognitive Chunks (V2)              | 0.0147        | 0.625   | 0.0251          | 0.464   |
| Number of Variable Repetitions (V3)         | -0.017        | 0.104   | -0.0225         | 0.0506  |

| Factor                                      | Recipe weight | p-value | Clinical weight | p-value |
|---------------------------------------------|---------------|---------|-----------------|---------|
| Explanation Length (V1)                     | 3.77          | 2.24E-34 | 3.3             | 5.73E-22 |
| Number of Output Terms (V1)                 | 1.34          | 0.0399  | 1.68            | 0.0198  |
| Number of Cognitive Chunks (V2)             | 8.44          | 7.01E-18| 4.6             | 1.71E-05 |
| Implicit Cognitive Chunks (V2)              | -15.3         | 2.74E-08| -11.8           | 0.000149 |
| Number of Variable Repetitions (V3)         | 2.4           | 0.000659| 2.13            | 0.0208  |

| Factor                                      | Recipe weight | p-value | Clinical weight | p-value |
|---------------------------------------------|---------------|---------|-----------------|---------|
| Explanation Length (V1)                     | -0.165        | 5.86E-16| -0.186          | 1.28E-19 |
| Number of Output Terms (V1)                 | -0.187        | 2.12E-05| -0.0335         | 0.444   |
| Number of Cognitive Chunks (V2)             | -0.208        | 1.93E-05| -0.0208         | 0.703   |
| Implicit Cognitive Chunks (V2)              | 0.297         | 0.0303  | 0.365           | 0.018   |
| Number of Variable Repetitions (V3)         | -0.179        | 5.71E-05| -0.149          | 0.000771 |
Figure 4: Response times across the six experiments. Responses were normalized by subtracting out subject mean to create centered values, and only response times for those subjects who got the question right are included. Vertical lines indicate standard errors.

**In general, greater complexity results in higher response times and lower satisfaction.** Increasing the number of lines, the number of terms within a line, adding new concepts, and repeating variables all increase the complexity of an explanation in various ways. In figure 4, we see that all of these changes increase response time. The effect of adding lines to scan results in the biggest increases in response time, while the effect of increasing the number of variable repetitions is more subtle. Making new concepts explicit also consistently results in increased response time. This effect may have partly been because adding a new concept explicitly adds a line, while adding it implicitly increases the number of terms in a line—and from V1, we see that the effect of the number of lines is larger than the effect of the number of terms. However, overall this effect seems larger than just adding lines (note the scales of the plots). Subjective scores appear to correlate inversely with complexity and response time.

Perhaps most unexpected was that participants both took longer and seemed less happy when new cognitive chunks were made explicit rather than implicitly embedded in a line—we might have expected that even if the explanation took longer to process, it would have been in some senses easier to follow through. It would be interesting to unpack this effect in future experiments, especially if participant frustration came from there now being multiple relevant lines, rather than just one. Future experiments could also highlight terms from the input in the explanation, to make it easier for participants to find the lines of potential relevance.
Figure 5: Subjective evaluation of explanations in three experiments. Participants were asked to rate each explanation from 1 to 10. Responses were normalized by subtracting out subject mean to create centered values.

**Different explanation variations had little effect on accuracy.** While there were strong, consistent effects from explanation variation on response time and satisfaction, these variations seemed to have much less effect on accuracy. There existed general decreasing trends in accuracy with respect to explanation length and the number of variable repetitions, and potentially some increasing trends with the number of new concepts introduced. However, few were statistically significant. This serves us as an interesting controlled comparison. In other words, we can now observe effects of different factors, holding the accuracy constant. The lack of effect may be because subjects were told to perform the task as quickly as they could without making mistakes, and our filtering also removed subjects prone to making many errors in the practice questions. Thus, the effect of a task being harder would be to increase response time, rather than decrease accuracy.

The differences in direction of the trends—some increases in complexity perhaps increasing accuracy, others decreasing it—are consistent with findings that sometimes more complex tasks force humans into slower but more careful thinking, while in other cases increased complexity can lead to higher errors [Kahneman, 2011]. Is it the case that the factors that resulted in the largest increases in response time (new concepts) also force the most concentration? While these experiments cannot differentiate these effects, future work to understand these phenomena may help us identify what kinds of increased complexities in explanation are innocuous or even useful and which push the limits of our processing abilities.
Trends are consistent across recipe and clinical domains In all experiments, the general trends in the metrics are consistent across both the recipe and clinical domains. Sometimes an effect is much weaker or unclear, but never is an effect clearly reversed. We believe this bodes well for there being a set of general principles for guiding explanation design, just as there exist design principles for interfaces and human-computer interaction. However, one small pattern can be noted in Figure 5, which shows lower satisfaction for the clinical domain than the recipe domain. This could be due to the fact that people felt more agitated about performing poorly in the medical domain than the clinical domain.

5 Discussion and Conclusion

Identifying how different factors affect a human’s ability to utilize explanation is an essential piece for creating interpretable machine learning systems—we need to know what to optimize. What factors have the largest effect, and what kind of effect? What factors have relatively little effect? Such knowledge can help us expand to faithfulness of the explanation to what it is describing with minimal sacrifices in human ability to process the explanation.

In this work, we investigated how the ability of humans to perform a simple task—verifying whether an output is consistent with an explanation and input—varies as a function of explanation size, new types of cognitive chunks and repeated terms in the explanation. We tested across two domains, carefully controlling for everything but the domain.

We summarized some intuitive and some counter intuitive discoveries—as any increase in explanation complexity increases response time and decreases subjective satisfaction with the explanation—some patterns were not so obvious. We had not expected that embedding a new concept would have been faster to process and more appealing than creating a new definition. We also found that new concepts and the number of lines increase response time more than variable repetition or longer lines. It would be interesting to verify the magnitude of these sensitivities on other tasks, such as forward simulation or counterfactual reasoning, to start building a more complete picture of what we should be optimizing our explanations for.

More broadly, there are many interesting directions regarding what kinds of explanation are best in what contexts. Are there universals that make for interpretable procedures, whether they be cast as decision sets, decision trees, or more general pseudocode; whether the task is verification, forward simulation, or counterfactual reasoning? Do these universals also carry over to regression settings? Or does each scenario have its own set of requirements? When the dimensionality of an input gets very large, do trade-offs for defining intermediate new concepts change? A better understanding of these questions is critical to design systems that can provide rationale to human users.

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**Description of Pilot Studies**

We conducted several pilot studies in the design of these experiments. Our pilot studies showed that asking subjects to respond quickly or within a time limit resulted in much lower accuracies; subjects would prefer to answer as time was running out rather than risk not answering the question. That said, there are clearly avenues of adjusting the way in which subjects are coached to place them in fast or careful thinking modes, to better identify which explanations are best in each case.

The experiment interface design also played an important role. We experimented with different placements of various blocks, the coloring of the text, whether the explanation was presented as rules or as narrative paragraphs, and also, within rules, whether the input was placed before or after the conclusion (that is, ‘if A: B” vs. “B if A”). All these affected response time and accuracy, and we picked the configuration that had the highest accuracy and user satisfaction.

Finally, in these initial trials, we also varied more factors: number of lines, input conjunctions, input disjunctions, output conjunctions, output disjunctions and global variables. Upon running...
preliminary regressions, we found that there was no significant difference in effect between disjunctions and conjunctions, though the number of lines, global variables, and general length of output clause—regardless of whether that length came from conjunctions or disjunctions—did have an effect on the response time. Thus, we chose to run our experiments based on these factors.