A Human-Centered Interpretability Framework Based on Weight of Evidence

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Abstract

In this paper, we take a human-centered approach to interpretable machine learning. First, drawing inspiration from the study of explanation in philosophy, cognitive science, and the social sciences, we propose a list of design principles for machinegenerated explanations that are meaningful to humans. Using the concept of weight of evidence from information theory, we develop a method for producing explanations that adhere to these principles. We show that this method can be adapted to handle high-dimensional, multi-class settings, vielding a flexible meta-algorithm for generating explanations. We demonstrate that these explanations can be estimated accurately from finite samples and are robust to small perturbations of the inputs. We also evaluate our method through a qualitative user study with machine learning practitioners, where we observe that the resulting explanations are usable despite some participants struggling with background concepts like prior class probabilities. Finally, we conclude by surfacing design implications for interpretability tools.

1. Introduction

Interpretability has long been a desirable property of machine learning (ML) models. With the success of complex models like neural networks, and their expanding reach into high-stakes and decision-critical applications, explaining ML models' predictions has become even more important. Interpretability can enable model debugging and lead to more robust ML systems, support knowledge discovery, and boost trust (Hong et al., 2020). It can also help to mitigate unfairness by surfacing undesirable model behavior (Tan et al., 2018; Dodge et al., 2019), lead to increased accountability by enabling auditing (Selbst & Barocas, 2018), and enable ML practitioners to better communicate model behavior to stakeholders (Veale et al., 2018; Hong et al., 2020).

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There are two primary techniques for achieving interpretability of ML models. The first is to train transparent, or glass-box, models that are intended to be inherently interpretable, such as decision trees (Quinlan, 1986) and sets (Lakkaraju et al., 2016), simple point systems (Zeng et al., 2017; Jung et al., 2017), and generalized additive models (Hastie & Tibshirani, 1990; Caruana et al., 2015). Although some researchers have argued that glass-box models should always be used in high-stakes scenarios (Rudin, 2019), complex *black-box* models, such as neural networks, random forests, and ensemble methods, are very widely used in practice. As a result, other ML researchers have gravitated towards interpretability methods that generate post-hoc *local* explanations for individual predictions produced by such models (e.g., Simonyan et al., 2013; Selvaraju et al., 2017; Ribeiro et al., 2016; Lundberg & Lee, 2017).

Local explanations aim to answer the question of why a model \mathcal{M} predicted a particular output y for some input x. There are many ways of operationalizing this abstract question, but most local interpretability methods address the proxy question of how much the value of each input feature x_i contributed to the prediction y. Thus, in practice, the explanations generated by many such methods consist of importance scores indicating the positive or negative relevance of each input feature x_i . Although the way these scores are computed varies from method to method, most start from an axiomatic or algorithmic derivation of some notion of feature importance, and only later investigate whether the resulting explanations are useful to humans. Some methods forgo this last step altogether, relying exclusively on intrinsic evaluation of mathematical properties of explanations, such as robustness or faithfulness to the underlying model (Alvarez-Melis & Jaakkola, 2018b).

Interpretability, however, is fundamentally a human-centered concept. As such, we put human needs at the center of both the design and evaluation of interpretability methods. Our work builds upon and weaves together two literatures that study the relationship between humans and explanations. First, researchers in philosophy, cognitive science, and the social sciences have long studied what it means to explain, and how humans do it (e.g., Pitt, 1988, and references therein). Second, a recent line of work within the human–computer interaction community has focused on how humans understand and utilize interpretability

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tools (i.e., software implementations of interpretability methods) (Lim & Dey, 2011; Bunt et al., 2012; Bussone et al., 2015; Hohman et al., 2019a; Lage et al., 2019; Abdul et al., 2020; Poursabzi-Sangdeh et al., 2021), where a common finding is that practitioners misunderstand, over-trust, and misuse these tools (e.g., Kaur et al., 2020).

We start by surveying the literature on the nature of explanation, revealing recurring characteristics of human explanation that are often missing from interpretability methods. We distill these characteristics into design principles that we argue human-centered machine-generated explanations should satisfy (Section 2). We then realize our design principles starting from the concept of weight of evidence (WoE) from information theory (Good, 1985), which has recently been advocated for by Spiegelhalter (2018), but, to the best of our knowledge, has yet to be investigated in the context of interpretability. In Section 3, we demonstrate that WoE can be adapted to handle high-dimensional, multi-class settings, yielding a suitable theoretical foundation for interpretability. We provide a general, customizable meta-algorithm to generate explanations for black-box models. We also show experimentally that WoE can be estimated from finite samples and is robust to small perturbations of the inputs (Section 4).

Evaluation of interpretability methods is notoriously difficult (Doshi-Velez & Kim, 2017; Kaur et al., 2020). Although recent work has focused on abstract, intrinsic metrics such as robustness or faithfulness to the underlying model (Alvarez-Melis & Jaakkola, 2018a), considerably less attention has been given to understanding how the resulting explanations are used in practice. This discrepancy between the intended use of the explanations—by a human, for a specific goal such as auditing, debugging, or building trust in a model—and their experimental evaluation—through abstract metrics, in generic settings—hampers understanding of the benefits and failure points of different methods. In Section 5, we build on a recent thread of work (Kaur et al., 2020; Vaughan & Wallach, 2020; Poursabzi-Sangdeh et al., 2021) that argues that evaluations should be grounded in concrete use cases and should put humans at the center, taking into account not only how they use interpretability tools, but how well they understand the principles behind them. We carry out an artifact-based interview study with ten ML practitioners to investigate their use of a tool implementing our meta-algorithm in the context of a practical task. Qualitative themes from this study suggest that most participants successfully used the tool to answer questions, despite struggling with background concepts like prior class probabilities. Although the study was designed to identify preferences for different tool modalities, participants often used all of them and requested the option to switch between them interactively. Our results additionally highlight the importance of providing well-designed tutorials for interpretability tools, even for experienced ML practitioners.

2. Human-Centered Design Principles

What it means to explain and how humans do it have long been studied in philosophy, cognitive science, and the social sciences. We draw on this literature to propose humancentered design principles for interpretability methods.

Hempel & Oppenheim (1948) and van Fraassen (1988) define an explanation as consisting of two main pieces: the *explanandum*, a description of the phenomenon to be explained, and the *explanans*, the facts or propositions that explain the phenomenon, which may rely on relevant aspects of context. As is often done colloquially, we will refer to the explanans as the *explanation*. Different ways of formalizing the explanation have given rise to various theories, ranging from logical deterministic propositions (Hempel & Oppenheim, 1948) to probabilistic ones (Salmon, 1971; van Fraassen, 1988). An excellent historical overview can be found in the surveys by Pitt (1988) and Miller (2019b).

In the context of local explanations for predictions made by ML models, the phenomenon to be explained is why a model \mathcal{M} predicted output y for input x. This why-question can be operationalized in different ways. The facts used to explain this phenomenon may include information about the input features, the model parameters, the data used to train the model, or the manner in which the model was trained.

Although the nature of explanation is far from settled, recurring themes emerge across disciplines. At the core of the theories by van Fraassen (1988) and Lipton (1990) is the hypothesis that humans tend to explain in contrastive terms (e.g., "a fever is more consistent with the flu than with a cold"), with explanations that are both factual and counterfactual (e.g., "had the patient had chest pressure too, the diagnosis would instead have been bronchitis"). Yet, the explanations produced by most current interpretability methods refer only to why the input x points to a single hypothesis (i.e., the prediction y) rather than ruling out all alternatives. In light of this, we propose our first two design principles:

- 1. Explanations should be contrastive, i.e., explicate why the model predicted y instead of alternative y'.
- 2. Explanations should be exhaustive, i.e., provide a justification for why every alternative y' was not predicted.

Another theme, featured prominently by Hempel (1962), is that human explanations decompose into simple components. In other words, humans usually explain using multiple simple accumulative statements, each addressing a few aspects of the evidence (e.g., "a fever rules out a cold in favor of bronchitis or pneumonia; among these, chills suggest the latter"). Each component is intended to be understood

¹Exceptions include recent work advocating for contrastive or counterfactual explanations (Wachter et al., 2017; Miller, 2019a; van der Waa et al., 2018), partly inspired by contrast sets (Azevedo, 2010; Bay & Pazzani, 1999; Webb et al., 2003; Novak et al., 2009).

without further decomposition. Again, this contrasts with current interpretability methods that explain in one shot, for example, by providing importance scores for all features simultaneously. Our next two design principles are therefore:

- Explanations should be modular and compositional, breaking up predictions into simple components.
- 4. Explanations should rely on easily-understandable quantities, so that each component is understandable.

Another recurring theme is minimality. In a survey of over 250 papers, Miller (2019b) argued that it is important, but underappreciated in ML, that only the most relevant facts be included in explanations. Thus, our final principle is:

5. **Explanations should be parsimonious**, i.e., only the most relevant facts should be provided as components.

These design principles are not exhaustive; each could be refined or generalized, and other principles could be derived from the same literature. However, we posit that these principles provide a reasonable starting point because they capture some of the most apparent discrepancies between human and machine-generated explanations. More generally, these principles point to a broader theme of human explanations as a *process* rather than (only) a *product* (Miller, 2019b; Lombrozo, 2012). Therefore, these principles work to shift interpretability methods from the latter towards the former.

3. Explaining with the Weight of Evidence

The set of design principles proposed in the previous section outlines a framework for human-centered interpretability in ML. In this section, we show how this framework can be operationalized by means of the *weight of evidence*, a simple but powerful concept from information theory. We operationalize the question of why model \mathcal{M} predicted output y for input x in terms of how much *evidence* each input feature x_i (or feature group) provides in favor of y relative to alternatives. An explanation based on this question adheres to our design principles because it is based on a familiar concept (evidence) that is grounded in common language, it naturally evokes a contrastive statement (evidence *for* or *against* something), and, as we explain below, it can be formalized using simple quantities that admit modularity.

3.1. Weight of Evidence: Foundations

The weight of evidence (WoE) is a well-studied probabilistic approach for analyzing variable importance that traces its origins back to Peirce (1878), but was popularized by Good (1950; 1968; 1985), whose definition and notation we follow here. Given a hypothesis and some evidence, the WoE seeks to answer the following question: "How much does the evidence speak in favor of or against the hypothesis?"

Let e denote the evidence, h a hypothesis, and \overline{h} its logical

complement. For exposition purposes, let us assume for now a binary classification setting, so that $e = (X_1, \ldots, X_n)$, h: Y = 1 and $\overline{h}: Y = 0$. The WoE of e in favor of h is the log-odds ratio between h conditioned on e and h marginally:

$$\operatorname{woe}(h:e) \triangleq \log \frac{O(h \mid e)}{O(h)},\tag{1}$$

where $O(\cdot)$ denotes the odds of a hypothesis, i.e.,

$$O(h) \triangleq \frac{P(h)}{P(\overline{h})}$$
 and $O(h \mid e) \triangleq \frac{P(h \mid e)}{P(\overline{h} \mid e)}$. (2)

Using Bayes' rule, woe(h : e) can also be defined as

$$\operatorname{woe}(h:e) \triangleq \log \frac{P(e \mid h)}{P(e \mid \overline{h})}.$$
 (3)

These two equivalent definitions provide complementary views of the WoE: the *hypothesis-odds* and *evidence-likelihood* interpretations. Using Equation (1), woe(h:e) > 0 indicates that the odds of h are higher under e than marginally. Equivalently, using Equation (3), it indicates that the likelihood of e is larger when conditioning on h than on its complement. In other words, the evidence *speaks in favor of* hypothesis h. Analogously, if woe(h:e) < 0 we would say that the evidence *speaks against* h. The quantities in Equations (1) and (3) are contrastive (cf. Principle 1)—that is, defined in terms of ratios.

As a concrete example, suppose that a doctor wants to know whether a patient's symptoms indicate the presence of a certain disease, say, the flu. Denote e= "the patient has a fever," h= "the patient has the flu," and $\bar{h}=$ "the patient doesn't have the flu." The doctor might know that for a patient, the odds of having the flu roughly double once the patient's fever is taken into account (i.e., the hypothesis-odds interpretation), which corresponds to woe(h:e) $\approx \log 2$. Alternatively, using the evidence-likelihood interpretation, the doctor could conclude that a patient is twice as likely to have a fever if they have the flu compared to when they do not. Note that neither interpretation tells us anything about the base rate of the flu.

The WoE generalizes beyond these simple scenarios. For example, it can be conditioned on additional information c:

$$\operatorname{woe}(h:e\mid c)\triangleq \log \frac{P(e\mid h,c)}{P(e\mid \overline{h},c)},$$

It can also contrast h to an arbitrary alternative hypothesis h' instead of \bar{h} (e.g., evidence in favor of "the flu" and against "a cold"): woe $(h/h':e) \triangleq \text{woe}(h:e \mid h \lor h')$. Thus, we can, in general, talk about the strength of evidence in favor of h and against h' provided by e (perhaps conditioned on e).

When the evidence is decomposable into multiple parts—that is, when $e=\bigcup_{i=1}^n e_i$ —the WoE is also decomposable:

$$\operatorname{woe}(h/h':e) = \sum_{i=1}^{n} \log \frac{P(e_i \mid e_{i-1}, \dots, e_1, h)}{P(e_i \mid e_{i-1}, \dots, e_1, h')}.$$
(4)

This property is crucial to defining an extension of the WoE to high-dimensional inputs that adheres to Principle 3 (modularity). We provide further properties of the WoE, along with an axiomatic derivation of the WoE, in the Appendix.

A further appealing aspect of the WoE is its immediate connection to Bayes' rule. For example, for binary classification, simple algebraic manipulation of the definition yields:

$$\underbrace{\log \frac{P(Y=1 \mid X)}{P(Y=0 \mid X)}}_{\text{Posterior log odds}} = \underbrace{\log \frac{P(Y=1)}{P(Y=0)}}_{\text{Prior log odds}} + \underbrace{\log \frac{P(X \mid Y=1)}{P(X \mid Y=0)}}_{\text{Weight of evidence}}. \quad (5)$$

This decomposition provides yet another interpretation of the WoE. A positive (respectively, negative) WoE implies that the posterior log odds of Y=1 versus Y=0 are higher (lower) than the prior log odds, indicating that the evidence makes Y=1 more (less) likely than it was a priori.

Equation (5) shows that the WoE is modular (cf. Principle 3) in another important way: it disentangles prior class probabilities and input likelihoods. This is important because of the *base rate fallacy* studied in the behavioral science literature (Tversky & Kahneman, 1974; Bar-Hillel, 1980; Eddy, 1982; Koehler, 1996). This cognitive bias, prevalent even among domain experts, is characterized by a frequent misinterpretation of posterior probabilities, primarily caused by a neglect of base rates (i.e., prior probabilities). Despite this, many interpretability methods do not explicitly display prior probabilities, and even when they do, they focus on explaining posterior probabilities, which invariably entangle information about priors and the input being explained.

Additionally, the units in which the WoE is expressed (logodds ratios) are arguably easily understandable (cf. Principle 4). There is evidence from the cognitive-neuroscience literature that log odds are a natural unit in human cognition. For example, it has been shown that degrees of confidence expressed by humans are proportional to log odds (Peirce & Jastrow, 1885), that people are less biased when responding in log odds that in linear scales (Phillips & Edwards, 1966), and there exist plausible neurological hypotheses for encoding of log odds in the human brain (Gold & Shadlen, 2001; 2002). We refer the reader to Zhang & Maloney (2012) for a meta-analysis of these various studies of log odds.

3.2. Composite Hypotheses and Evidence

Traditionally, the WoE has been mostly used in simple settings, such as a single binary output and only a few input features. Its use in the more complex settings typically considered in modern ML therefore poses new challenges.

The first such challenge is that in multi-class classification there is flexibility in choosing the hypotheses h and h' to contrast. The obvious choice of letting h correspond to the predicted class y^* and h' its complement is unlikely to yield useful explanations when the number of classes is large (e.g., explaining the evidence in favor of one disease and against around one hundred thousand other possibilities). Following Principle 3 (modularity), and taking inspiration from Hempel's model (1962) and the view of explanation as a process (Lombrozo, 2012; Miller, 2019b), we address this by casting explanation as a sequential procedure, whereby a subset of the possible outcomes is ruled out at each step. For example, in medical diagnosis, we might want to first explain why bacterial diseases were ruled out in favor of viral ones, and then explain why a specific viral disease was predicted instead of the others. In general, for a classification problem over labels $Y = \{1, ..., k\},\$ we will consider a (given or constructed) nested partitioning of Y into a sequence of T-many subsets U_i of classes such that: $\{y^*\} \triangleq \mathsf{U}_T \subset \mathsf{U}_{T-1} \subset \cdots \subset \mathsf{U}_0 \triangleq \mathsf{Y}.$ This partition implies a sequence of pairs of hypotheses $(h_t, h'_t) = (y \in U_t, y \in U_{t-1} \setminus U_t)$ (see Appendix, Figure 4).

A second challenge arises when the the number of input features is large. For very high-dimensional inputs (such as images or detailed health records), providing a WoE value for each feature will rarely be informative. Again, imagine our hypothetical doctor having to simultaneously analyze the relevance of thousands of symptoms. For such cases, we propose aggregating the input features into feature groups (e.g., super-pixels for images or groups of related symptoms for medical diagnosis). Formally, for an input X of dimension n, we partition the feature indices into m disjoint subsets, with $S_1 \cup \cdots \cup S_m = \{1, \ldots, n\}$. Equation (4) (or, equivalently, the chain rule of probability) allows for arbitrary groupings, so for any such partition we can compute

$$\operatorname{woe}(h/h':X) = \sum_{i=1}^{m} \underbrace{\log \frac{P(X_{S_{i}} | X_{S_{i-1}}, ..., X_{S_{1}}, h)}{P(X_{S_{i}} | X_{S_{i-1}}, ..., X_{S_{1}}, h')}}_{=\operatorname{woe}(h/h':X_{S_{i}} | X_{S_{i}}, ..., X_{S_{1}}, h')}$$
(6)

where $X_{S_i} = \{X_j\}_{j \in S_i}$ is the *i*th feature group, or "atom."

3.3. A Meta-Algorithm for WoE Explanations

Using these extensions of the WoE, we propose a metaalgorithm for generating explanations for complex classifiers (Algorithm 1). Given a model, an input, and a prediction, the algorithm generates an explanation for the prediction sequentially by producing WoE values for progressively smaller nested hypotheses. Specifically, at every step t, a subset of classes $U_t \subset U_{t-1}$ is selected and the remaining classes $\overline{U}_t = U_{t-1} \setminus U_t$ ruled out. The user is shown a comparison of hypotheses $h_t : y \in U_t$ and $h'_t : y \in \overline{U}_t$ consisting of both their prior odds $\pi(U_t)$ (computed in line 9) and

Algorithm 1 WoE meta-algorithm for complex models

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1: Input: Instance X \in \mathbb{R}^n, prediction y^* \in \{1, \dots, k\}
  2: Parameters: Features A = \{\{1\}, \dots, \{n\}\} or feature
        groups \mathcal{A} = \{S_1, \dots, S_m\}
  3: Initialize U_0 \leftarrow \{1, \dots, k\}
  4: t \leftarrow 0
  5: while |U_t| > 1 do
  6:
             t \leftarrow t + 1
             U_t \leftarrow SelectHypothesis(U_{t-1}, y^*)
  7:
             \begin{array}{l} \overline{\mathsf{U}}_t \leftarrow \mathsf{U}_{t-1} \setminus \mathsf{U}_t \text{ \{relative complement\}} \\ \pi(\mathsf{U}_t) \leftarrow \log \frac{P(y \in \overline{\mathsf{U}}_t)}{P(y \in \overline{\mathsf{U}}_t)} \text{ \{prior log-odds\}} \end{array}
  8:
  9:
             for i=1,\ldots,|\mathcal{A}| do
10:
                  \omega_i^t \leftarrow \text{woe}(y \in U_t/y \in \overline{U}_t : X_{A_i} \mid X_{A_{i-1}}, \dots, X_{A_1})
11:
12:
             end for
             \Omega_t \leftarrow \sum_{i=1}^{|\mathcal{A}|} \omega_i^t
13:
             DisplayExplanation(\mathsf{U}_t, \overline{\mathsf{U}}_t, \mathcal{A}, \pi(\mathsf{U}_t), \{\omega_i^t\}_i, \Omega_t)
14:
15: end while
```

the WoE in favor of h_t and against h_t' . WoE values are computed sequentially with each atom \mathcal{A}_i (either an individual input feature or a group of features) as the evidence (line 11) and these values are summed to obtain the total WoE using the additive property (line 13). These values are presented to the user, and the process continues until all classes except the prediction y^* have been ruled out (cf. Principles 2-3).

Left unspecified in this meta-algorithm are four key choices that are application-dependent and require further discussion. First is the question of how to define the SelectHypothesis method to progressively partition the classes (line 7). If there is an inherent natural partitioning (e.g., "viral" versus "bacterial," as in the example discussed previously), then SelectHypothesis simply amounts to retrieving the largest subset in the partition containing the prediction y^* . For the general case, we propose selecting the hypothesis that maximizes a WoE-based objective:

$$\mathsf{U}_t \leftarrow \underset{\mathsf{U} \subset \mathsf{U}_{t-1}; y^* \in \mathsf{U}}{\operatorname{argmax}} \operatorname{woe}(y \in \mathsf{U} \, / \, (y \in \mathsf{U}_{t-1} \backslash \mathsf{U}) : X) - R(\mathsf{U}),$$

where R is a cardinality-based regularizer. R should be chosen to penalize sets that are too small (which would yield granular explanations with many steps, in opposition to Principle 5) or too large (which would yield coarse explanations, to the detriment of Principle 3). Although the choice of R should ideally be informed by the application and the user, a sensible generic choice is $R(\mathsf{U}) \propto \left| |\mathsf{U}| - \frac{1}{2} |\mathsf{U}_{t-1}| \right|^p$, normalized so that $R(\mathsf{U}) \in [0,1]$. Using this regularizer, Algorithm 1 approximately splits the remaining classes in half at every step, yielding roughly $O(\log k)$ steps in total.

Second, it should be noted that lines 10–12 in Algorithm 1 implicitly assume an ordering of the atoms, and that this ordering might affect the WoE values. In some applications, there might be a conditional independence structure known

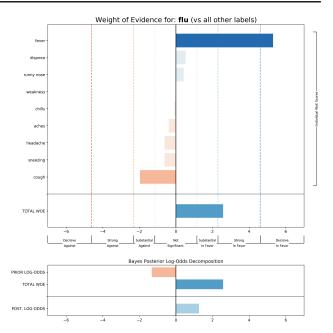


Figure 1. One step of an explanation produced by our tool.

a priori that could inform the choice of atoms and their ordering (e.g., those simplifying the conditioning in line 11 the most). If not, the ordering can again be chosen randomly or based on the sorted per-atom conditional WoE values.

Third, the meta-algorithm requires access to the conditional likelihoods $P(X_{A_i}|X_{A_{i-1}},\ldots,X_{A_1},Y)$ to compute the per-atom WoE (line 11). Depending on the type of model and data, there are four possible scenarios. In the best case, the model computes all necessary conditional likelihoods internally. If instead it computes only marginal feature likelihoods $P(X_{A_i}|Y)$, we can use a naïve Bayes (NB) approximation—that is, use these in place of the conditional likelihoods in Equation (6). If the model is a black box or does not compute likelihoods internally, then these must be estimated from samples. In some settings it might be feasible to fit a conditional likelihood estimation (e.g., autoregressive) model. If this is intractable, we can use a NB approximation here too, fitting only the marginal likelihoods (e.g., via a Gaussian NB model). The likelihood estimation model must be fitted only once, potentially offline. We further discuss estimation in Appendix F and explore the quality of finite-sample WoE estimation experimentally in Section 4.1.

Finally, there is the question of how to implement Display-Explanation. When the number of atoms is large, the WoE values for only the most salient atoms can be displayed (cf. Principle 5)—for example, those with absolute WoE larger than a given threshold τ ; Good (1985) suggests $\tau=2$ as a rule of thumb. Otherwise, all per-atom WoE values can be displayed along with the total WoE and prior log odds.

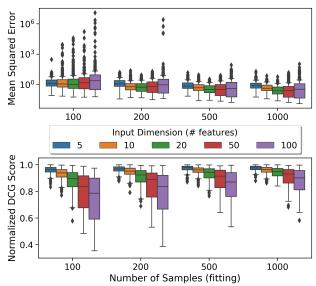


Figure 2. Quality of WoE estimation. Top: MSE. Bottom: NDCG, ranging from 0 (worst) to 1 (perfect) ranking quality.

An example single-step explanation produced by our method (on fabricated data from our user study tutorial) is shown in Figure 1. The sorting and color coding of the features by their WoE value makes it apparent which contribute the most evidence in favor of or against the predicted class "the flu," and the labeling along the x-axis provides guidelines for context. The visualization suggests the additive nature of these values (i.e., that stacking blue bars and subtracting red ones yields the total WoE). The bottom panel, a graphical representation of Equation (5), disentangles the model's estimated prior class odds (which disfavor the flu), from its total WoE (strongly in favor of the flu), showing that the evidence provided by the features is strong enough to overcome unfavorable prior odds and ultimately predict the flu.

In the Appendix, we draw an analogy between how WoE explanations relate to other post-hoc interpretability methods and the relationship between generative and discriminative models (Appendix C); we show that the WoE has simple analytic expressions for popular model families (Appendix D); and we also discuss use cases and limitations (Appendix E).

4. Quantitative Experiments

Here, we assess the quality of finite-sample WoE estimation and the robustness of the WoE to perturbations of the inputs.

4.1. Quality of Finite-Sample WoE Estimation

Our first experiment evaluates the quality of WoE estimates from finite samples. As explained above, such estimates are needed if the model is a black box or does not explicitly compute likelihoods. For evaluation purposes, we consider a model that, by construction, computes all the quantities required for exact WoE computation, but treat it as black box—that is, its internal WoE computation will be used only for evaluation, and is not available to our interpretability method. Instead, we separately fit a likelihood estimation model by querying the model for a small number of inputs, and use this estimation model to compute WoE values at explanation time. Furthermore, we control for model specification by having both the model and our likelihood estimation model use the naïve Bayes assumption. Specifically, we use a smoothed Gaussian naïve Bayes (GNB) classifier. This allows us to focus on the quality of WoE estimation from finite samples, but does not address model misspecification.

First, we generate a dataset of a given dimension. We train a classifier on a subset of this dataset of size $N_{\rm train}=1000$ and fit the WoE likelihood estimation model on a separate subset of size $N_{\rm fit}$, which we vary. For every test example x_i ($N_{\rm test}=10$), we compute true WoE values for each input feature using the model's prior and posterior probabilities, and then compute estimated WoE values according to the estimation model in Appendix F. We compare these using two metrics: mean squared error and normalized discounted cumulative gain (NDCG), a measure of ranking quality that might be relevant to practitioners, applied to the relative ranking of input features by their (true or estimated) WoE.²

Figure 2 shows these metrics of estimation quality as a function of input dimension and sample size $N_{\rm fit}$. As expected, estimation quality improves with the number of samples used for fitting, and degrades gracefully as the input dimension increases. These results suggest that the WoE can be accurately estimated—even in relatively high dimensions—from finite samples, though we caution that these results may look different for other models, and we do not measure the approximation error due to the NB approximation.

4.2. Robustness of WoE

Previous work has argued that interpretability methods should be robust in the sense that the explanations they provide should not vary dramatically when the input whose prediction is being explained changes by a small amount. To investigate the robustness of our method, we follow the set-up of Alvarez-Melis & Jaakkola (2018a). Letting $\mathcal{E}(\cdot)$ be a function that maps feature vectors $x \in \mathbb{R}^n$ to explanation vectors (e.g., importance scores) $e \in \mathbb{R}^n$, we quantify its robustness around x_0 through its local Lipschitz constant:

$$L(x_0) = \max_{x_j \in \mathcal{B}_{\varepsilon}(x_0)} \frac{\|\mathcal{E}(x_j) - \mathcal{E}(x_0)\|}{\|x_j - x_0\|},$$
 (7)

where $\mathcal{B}_{\varepsilon}(x_0) = \{x \mid ||x - x_0|| \leq \varepsilon\}$. Intuitively, $L(x_0)$ quantifies the largest relative change in importance scores in a small neighborhood around x_0 . Extreme values are

²The NDCG is only defined for positive values, so we compute it separately for positive and negative values and average them.

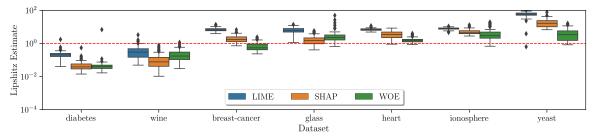


Figure 3. Explanation robustness across benchmark datasets. Extreme values away from L=1 (dashed line) are undesirable.

usually undesirable, as they indicate explanations that are either too sensitive (large L) or not responsive enough (very small L) to changes in the input features. In most settings, values below 1 but bounded away from 0 are preferable.

Concretely, we first train a GNB classifier in advance. Then, for any input x we use the classifier to generate a prediction y, and input both of these to our method to generate $\mathcal{E}(x)$, a vector of WoE values for each feature x_i . Since computing the robustness metric (7) involves maximization, we estimate this quantity from finite samples using Bayesian optimization, making repeated calls to $\mathcal{E}(\cdot)$. We focus on standard benchmark classification datasets from the UCI repository (Dua & Graff, 2017), and compare against two popular interpretability methods, LIME (Ribeiro et al., 2016) and SHAP (Lundberg & Lee, 2017). Figure 3 shows results on ten repetitions with different random seeds for each interpretability model and dataset pair. The red dashed line indicates the bound L(x) = 1. In all but one dataset, WoE explanations are on average as close or closer to the ideal Lipschitz robustness as those generated by LIME and SHAP.

5. User Study

To evaluate the usefulness of our method in the types of scenarios in which it would be employed in practice, we implemented the method in a simple tool and used it to conduct an artifact-based interview study with ten ML practitioners. We chose this qualitative approach to capture nuanced feedback about the tool's features and the clarity of its explanations, allowing us to distinguish between our intended use of the tool and participants' mental models (Gibson, 1977; Norman, 2013). In such qualitative studies, one typically opts for a relatively small sample size in order to allow extended time and data collection per participant (Hudson & Mankoff, 2014; Olsen Jr, 2007; Turner et al., 2006). Our study followed a "think-aloud" protocol in which participants were asked to verbalize their thought process as they used the tool to perform specific tasks. We placed participants in a controlled setting rather than observe them using the tool on their own models because of challenges including data access, inconsistencies in the types of data being analyzed, and potential difficulty in establishing patterns across settings.

Our study consisted of two parts: a tutorial to introduce the concepts and functionalities needed to use our tool, followed by the main study in which participants answered questions about a pretrained ML model using the tool. The main study was designed to let us observe the use of the two extensions of the WoE described in Section 3.2: feature groups and sequential explanations. We also conducted a pre-study interview to establish participants' background in ML and a post-study interview in which participants recounted their experience with the tool and how they might use it in their ML pipelines. The study design was approved by our internal IRB. More details are included in Appendix G.

We established the accuracy of participants' open-ended answers based on consensus between two of the authors. To examine the usability of our tool, participants' interpretability needs, and their general impressions, we analyzed transcripts of the recording of each participant for high-level themes using inductive thematic analysis (Braun & Clarke, 2012) and affinity diagramming. These themes offer preliminary evidence of patterns of tool use, as we describe below.

Understanding of Relevant Concepts. Our analysis of the pre-study interviews and answers to checkpoint questions in the tutorial provide insight into participants' understanding of concepts relevant to the WoE. Strikingly, we found that most participants (7/10) struggled to understand and use prior class probabilities in the tutorial. The section on this topic was time-consuming: participants spent a third of their tutorial time on this section on average. Eventually, most participants either ignored the prior class probabilities or used them incorrectly, supporting the base rate fallacy. Nonetheless, participants were able to answer questions in the main study for which prior class probabilities were relevant. This raises the possibility that while they struggled with the abstract concept, they were able to use the information indirectly (e.g., via displayed class probabilities).

Although participants generally understood the concept of WoE, some confused negative WoE values with negative values for input features, thus finding it challenging to make sense of the explanations. As a result, two participants provided incorrect answers for questions in the main study.

Tool Usability and User Preferences. Participants had no

overwhelming preference between input features versus feature groups in the explanations. Indeed, they noted that the two levels of granularity provide complementary information, and switching between the two options was a clear pattern across all participants. Although feature groups provide a high-level overview making it "easier to manage [reading the plot]...[and the] direction of analysis is a lot clearer" (P8), feature-level explanations help participants in "looking into more details in general...to know exactly which feature it was [that was responsible for a prediction]" (P10). We observed some differences in behavior based on participants' roles and expertise, though of course these are inconclusive with our small sample size. Participants with more ML experience tended to rely on feature-level plots, while those with customer-facing jobs more often provided high-level answers based on feature groups, noting that groups "provide customer-friendly explanations" (P8).

Participants found sequential explanations to be a helpful breakdown of a larger explanation into parts. P3 noted these were like a "story of how the prediction was made." Sequential explanations prompted more detailed answers to our questions and most participants (7/10) accurately answered questions in part 2 of the study using sequential explanations. They explained that the type of questions in part 2—which required understanding how each of the classes were ruled out—could not be answered via one-shot explanations. P8 commented, "I guess without this breaking it down to this point I wouldn't have thought twice really about this [input feature group] being a [differentiating] factor between the two [output classes]... this goes a lot deeper than I probably could have gone just looking at that without the tool."

Although most participants were happy with the level of detail presented, some participants with more ML experience expressed a desire for deeper understanding of how the explanations were generated. They understood the underlying concepts, but were wary of anything that appeared automated, including the breakdown of class comparisons in sequential explanations (which was automated) and the feature groups (which were actually manually generated).

Although participants said that the tool helped them understand the model's predictions, not all of them envisioned the tool being added to their ML pipelines. Participants with significant prior ML experience already had established ways of ensuring that model predictions are reasonable, but recognized other exciting use cases for the tool, such as communicating complex predictions to less experienced end users. Particularly for high-risk domains, visualizations from the tool could help users probe odd predictions. P7 noted, "With my focus on medical data, I do see the need in working with a customer...there this [tool] would be a must-have."

General Needs for Interpretability Tools. Most interpretability tools, including ours, rely on tutorials or code

documentation to provide an introduction to the tool's concepts and functionalities. All participants appreciated the information presented in our tutorial: "I can't imagine doing this [study] without the tutorial. I generally know a lot more about these concepts now" (P5). The tutorial seemed to impact participants' overall accuracy in answering the main study questions— those who spent longer on the tutorial tended to provide more accurate and more thoughtful answers. This manifested as longer time spent on exploring the tool in the tutorial and ensuring that their answers to the checkpoint questions were accurate and thorough.

Finally, participants expressed a desire to be able to more easily switch between different options (e.g., input features versus feature groups) rather than re-running code. Interactivity was consequently the most commonly requested functionality in the post-study interview. This is in line with prior work on human-centered design principles for ML (Amershi et al., 2019; Hohman et al., 2019b; Weld & Bansal, 2019).

6. Discussion

Drawing on studies of explanation in philosophy, cognitive science, and the social sciences, we propose human-centered design principles for machine-generated explanations. We then propose a framework to realize these principles based on *weight of evidence*, and show how WoE can be adapted to fit the needs of high-dimensional, multi-class settings.

One limitation of our framework is that computing WoE values requires access to model conditional likelihoods. When these are unavailable directly, they must be estimated from finite samples, as explored in Section 4.1: doing so efficiently in very high dimensions (e.g., for images) is an active area of research. New advances could be ported to scale up WoE estimation to such domains. Additional work is also needed to understand the impact on users of various choices left open in our meta-algorithm, such as the partitioning of classes and the ordering of input features or feature groups.

The findings from our user study offer important lessons that we believe are generally applicable to other interpretability tools. Chief among these is the importance of user-friendly and engaging tutorials that provide users with the necessary understanding of the tool and its intended usage, and users' desire for flexibility in tools. These results underscore the importance of putting human needs at the center of both the design and evaluation of interpretability methods.

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A. Design Principles in Further Detail

In Section 2, we surveyed the literature on the nature of explanation from philosophy, cognitive science, and the social sciences, leading us to propose a list of design principles for machine-generated explanations that are meaningful to humans. In this section, we further discuss these principles.

D1. Explanations should be contrastive. A recurring theme across disciplines is the hypothesis that humans tend to explain in contrastive terms. We therefore argue that machine-generated explanations should also be contrastive. In other words, the *explanandum* should be the question of why a model \mathcal{M} predicted a particular output y for some input x instead of predicting y'. However, most current interpretability methods do not explicitly refer to an alternative y', implicitly assuming it to be the complement of y.

D2. Explanations should be exhaustive. The explanations produced by most current interpretability methods refer only to why the input x points to a single hypothesis (i.e., the prediction y) rather than ruling out all alternatives. However, human explanations tend to provide a justification for why every alternative y' was not predicted. This is important for (at least) two reasons: First, it is necessary for generating explanations that are counterfactual. Second, it entails explanations that are, to use Hempel's terminology, complete. For example, an explanation for a diagnosis of pneumonia based solely on the presence of a cough is not exhaustive because a cough is a symptom of other diseases too.

D3. Explanations should be modular and compositional.

Explanations are most needed for the predictions of complex black-box models like neural networks. Yet, when used in these settings, most current interpretability methods generate a single, high-dimensional static explanation for each prediction (e.g., a heatmap for a prediction made by an image classifier). Explanations like these can be difficult to understand and draw conclusions from, particularly for non-expert users. In addition, this approach differs from human explanations, which tend to decompose into simple components (Hempel, 1962). We therefore argue that machine-generated explanations should also explain using multiple simple accumulative statements, each addressing a few aspects of the evidence. We note, however, that this type of modularity introduces an inherent tradeoff between the number of components in an explanation (too many components might be difficult to understand simultaneously) and their relative complexity (simpler components are easier to draw conclusions from, but using simpler components may mean that more of them are needed). Breaking up predictions into simple components also helps shift interpretability

methods from treating explanations as a product towards explanations as a process (Lombrozo, 2012; Miller, 2019b).

D4. Explanations should rely on easily-understandable quantities. Explanations are only as useful as the information that they provide to users. We therefore argue that explanations should rely on quantities that can be easily understood, thereby making it less likely that users will misunderstand them, potentially leading to misuse (Kaur et al., 2020).

D5. Explanations should be parsimonious. As noted by Miller (2019b), one of the most salient recurring themes in the literature on human explanation is minimality—i.e., only the most relevant facts should be included in explanations. We therefore argue that explanations should adhere to Occam's Razor, which states that the simpler of two equally good explanations should always be preferred. Furthermore, if omitting less-relevant facts makes a machine-generated explanation easier to understand while remaining equally faithful to the underlying model, then they should be omitted.

B. Axiomatic Derivation of the WoE

As we described in Section 1, interpretability is fundamentally a human-centered concept. As such, human needs should therefore be at the center of both the design and evaluation of interpretability methods. We achieve this by first proposing a list of design principles that we argue humancentered machine-generated explanations should satisfy and then realizing these design principles starting from the concept of weight of evidence (WoE). However, the WoE also has an axiomatic derivation, which we include below.

Good (1985) provides an axiomatic derivation for the WoE of e in favor of h), as defined in Equation (1). This derivation shows that it the WoE is (up to a constant) the only function F of e and h that satisfies the following properties:

- 1. F(e, h) depends only on $P(e \mid h)$ and $P(e \mid \overline{h})$.
- 2. $P(h \mid e)$ is a function of only P(h) and F(e, h).
- 3. When e is decomposable, F(e,h) is additive in terms of e, e.g., $F(e_1 \wedge e_2, h) = F(e_1, h) + F(e_2, h)$.

We note that all three of these properties are fairly general. For example, the second property is a reasonable requirement for any probabilistic model of feature importance. Meanwhile, the first property is a sufficient (although not a necessary) condition for obtaining contrastive explanations.

C. Relationship Between WoE Explanations and Other Interpretability Methods

When viewed from a probabilistic perspective, most post-hoc interpretability methods revolve around a model's

³Not to be confused with *complete* according to the terminology of Goodman et al. (2006), where all variables are explained.

predictive posterior $P_{\mathcal{M}}$ —that is, they seek explanations that deconstruct $P_{\mathcal{M}}(Y=y^*\mid X)$ in various ways. For example, LIME (Ribeiro et al., 2016) seeks to approximate $f(x)=P_{\mathcal{M}}(Y\mid X=x)$ in the vicinity of x_0 through a simpler, interpretable surrogate model $\tilde{f}(x)$. Similarly, SHAP (Lundberg & Lee, 2017) quantifies variable importance by analyzing the effect on the posterior of "dropping" variables X_i from the input X. In contrast, the WOE focuses—directly, in the case of the evidence-likelihood interpretation and indirectly in the case of the hypothesis-odds interpretation—on the conditional likelihood $P(X=x\mid Y)$. In other words, for a given input x, a WoE explanation is based on the probability assigned by the model to x (or a subset of its features) given, e.g., $Y=y^*$.

When viewed in this way, the relationship between WoE explanations and other post-hoc interpretability methods like LIME and SHAP is akin to the relationship between generative and discriminative models. Indeed, as is the case for some pairs of generative and discriminative models (e.g., naïve Bayes and logistic regression), these different interpretability methods also turn out to be equivalent—two sides of the same coin—for some simple classifiers, as shown in Appendix D for logistic regression. However, this is not generally the case. Moreover, even when the explanations generated by different interpretability methods qualitatively agree (i.e., the same features are highlighted as being important), the specific interpretations of the explanations will differ. Indeed, the WoE uses a different operationalization of the why-question described in Section 2, in turn entailing different units of explanation: log likelihoods and log odds ratios in the case of the WoE and linear attribution scores for posterior probabilities in the case of LIME and SHAP.

D. Well-Known Model Families

In this section, we show that for well-known families of simple classifiers, the WoE has a closed-form expression. Consider a binary classification setting—i.e., $y \in \{0,1\}$ —with n input features—i.e., $x=(x_1,\ldots,x_n)$ —and, for conciseness, let $p_1=P(Y=1)$ and $p_0=P(Y=0)$.

D.1. Logistic Regression

For logistic regression, the predictive posterior is

$$P(Y = 1 \mid X) = \sigma(w^{\top}x + w_0) \in [0, 1],$$

where $\sigma(t)=\frac{e^t}{e^t+1}=\frac{1}{1+e^{-t}}$ is the sigmoid function. Logistic regression already has a natural log-odds interpretation:

$$\log \frac{P(Y=1 \mid X)}{P(Y=0 \mid X)} = \frac{\sigma(w^{\top}x + w_0)}{1 - \sigma(w^{\top}x + w_0)}$$
$$= \log e^{w^{\top}x + w_0} = w^{\top}x + w_0.$$

From this, the WoE is easy to compute and unsurprising:

$$\begin{split} \text{woe}(Y = 1: X = x) &= \log \frac{P(Y = 1|X)}{P(Y = 0|X)} / \log \frac{P(Y = 1)}{P(Y = 0)} \\ &= w^{\top} x + w_0 - \log \frac{p_1}{p_0}. \end{split}$$

Therefore, the WoE for logistic regression can be interpreted as removing the effect of the base rate (via the log-odds ratio $\log \frac{p_1}{p_0}$) from the linear attribution model (i.e., $w^{\top}x + w_0$).

Unfortunately, obtaining closed-form expressions for perfeature WoE values is not as simple. Because logistic regression is not a generative model, it does not explicitly model the conditional probabilities needed to obtain these values. For example, neither $P(Y=1\mid X_i)$ or $P(X_i\mid Y=1)$ can be unambiguously obtained from $P(Y=1\mid X)$. To determine these conditional probabilities, assumptions must be made. For example, the simplest coherent identification of the coefficients with per-feature log-likelihood ratios is:

$$w_0 = \log \frac{p_1}{p_0}$$

$$w_i x_i + w_0 = \log \frac{P(Y = 1 \mid x_i)}{P(Y = 0 \mid x_i)}.$$

However, this identification makes the assumption that the coefficients do not model feature interactions. Under this identification, the WoE value for X_i is then as follows:

$$woe(Y = 1 : X_i) = w_i x_i.$$

This is a natural notion of feature importance for log-linear models under a conditional independence assumption. The posterior log odds of Y = 1 versus Y = 0 is then given by:

$$\log \frac{P(Y=1|X)}{P(Y=0|X)} \\ = \sum_{i=1}^{n} \text{woe}(Y=1:x_i) + \log \frac{p_1}{p_0} = w^{\top}x + w_0.$$

Other post-hoc interpretability methods can be shown to recover logistic regression's coefficients too. For example, it is easy to show that without penalization, with a logistic link function, and asymptotically in the number of fitting samples, LIME (Ribeiro et al., 2016) would find a surrogate model that coincides with the true log-linear model, so the resulting explanations would coincide with the WoE values.

D.2. Naïve Bayes

The equivalence between the WoE and naïve Bayes (NB) is well known, but we revisit it here for completeness. An NB classifier already assumes conditional independence:

$$P(X_i \mid Y) \perp P(X_i \mid Y) \quad \forall i \neq j.$$

The conditional probabilities are modeled as

$$p(Y = 1|X) = P(Y = 1) \prod_{i=1}^{n} P(X_i \mid Y = 1),$$

where $P(X_i \mid Y)$ is estimated during training. Therefore, for a NB classifier, the total WoE is defined as follows:

$$\begin{aligned} \text{woe}(Y = 1: X) &= \log \frac{P(X \mid Y = 1)}{P(X \mid Y = 0)} \\ &= \log \frac{\prod_{i=1}^{n} P(X_i \mid Y = 1)}{\prod_{i=1}^{n} P(X_i \mid Y = 1)} \\ &= \sum_{i=1}^{n} \log \frac{P(X_i \mid Y = 1)}{P(X_i \mid Y = 0)}. \end{aligned}$$

In addition,

$$woe(Y = 1 : X_i) = woe(Y = 1 : X_i | X_0, ..., X_{i-1})$$

= $\log \frac{P(X_i | Y = 1)}{P(X_i | Y = 0)}$.

A Gaussian naïve Bayes (GNB) classifier would parameterize the conditional likelihoods as *n*-dimensional Gaussians:

$$p(X \mid Y = k) = \frac{1}{\sqrt{(2\pi)^n |\Sigma_k|}} \exp\left\{-\frac{1}{2}(x - \mu_k)^\top \Sigma_i^{-1}(x - \mu_k),\right\}$$

where the covariance matrix Σ_k is diagonal in order to satisfy the NB assumption. This then implies the following:

$$p(X_i \mid Y = k) = \frac{1}{\sqrt{(2\pi)^n [\Sigma_k]_{ii}}} \exp\left\{-\frac{1}{2[\Sigma_k]_{ii}} |x_i - \mu_{ki}|^2\right\}.$$

Therefore,

$$\begin{split} &\operatorname{woe}(Y=1:X_{i}) \\ &= \log \left(\frac{[\Sigma_{0}]_{ii}}{[\Sigma_{1}]_{ii}} \right)^{1/2} \exp \left\{ -\frac{1}{2} \left(\frac{1}{[\Sigma_{1}]_{ii}} |x_{i} - \mu_{1,i}|^{2} \right. \right. \\ &\left. - \frac{1}{[\Sigma_{0}]_{ii}} |x_{i} - \mu_{0,i}|^{2} \right) \right\} \\ &= -\frac{1}{2} \left(\frac{1}{[\Sigma_{1}]_{ii}} |x_{i} - \mu_{1,i}|^{2} - \frac{1}{[\Sigma_{0}]_{ii}} |x_{i} - \mu_{0,i}|^{2} \right) \\ &- \frac{1}{2} \log \frac{[\Sigma_{1}]_{ii}}{[\Sigma_{0}]_{ii}} \end{split}$$

and

$$\begin{split} & \operatorname{woe}(Y = 1:X) \\ &= -\frac{1}{2} \bigg(x^\top (\Sigma_1^{-1} - \Sigma_0^{-1}) x - 2 (\mu_1^\top \Sigma_1^{-1} - \mu_0^\top \Sigma_0^{-1}) x \\ &+ (\mu_1^\top \Sigma_1^{-1} \mu_1 - \mu_0^\top \Sigma_0^{-1} \mu_0) \bigg) - \frac{1}{2} \log \frac{|\Sigma_1|}{|\Sigma_0|}. \end{split}$$

This implies that $woe(Y = 1 : X_i) > 0$ if and only if:

$$\frac{1}{\Sigma_{1,ii}}|x_i - \mu_{1,i}|^2 - \log \Sigma_{1,ii} < \frac{1}{\Sigma_{0,ii}}|x_i - \mu_{0,i}|^2 - \log \Sigma_{0,ii}.$$

In other words, woe $(Y=1:X_i)>0$ if and only if x_i is closer (according to a variance-normalized distance) to $\mu_{1,i}$ than to $\mu_{0,i}$. Similarly, the total WoE satisfies the following:

$$\begin{aligned} \operatorname{woe}(Y = 1 \mid X) &> 0 \Longleftrightarrow \\ d_{\Sigma_1}^2(x, \mu_1) &- d_{\Sigma_0}^2(x, \mu_0) &< \log \frac{|\Sigma_1|}{|\Sigma_0|}, \end{aligned}$$

where d_{Σ} is the Mahalanobis distance with covariance Σ .

D.3. LDA and QDA

Linear discriminant analysis (LDA) and quadratic discriminant analysis (QDA) are similar to Gaussian naïve Bayes, except that they do not make a conditional independence assumption—i.e., the covariance matrix need not be diagonal. Although non-conditional per-feature WoE values can still be computed easily (because marginalizing a multivariate Gaussian boils down to taking subsets of the mean and covariance matrix), the conditional per-feature WoE values do not have as simple an expression. In the general case, where the variables are not independent, if $X \mid Y \sim \mathcal{N}(\mu, \Sigma)$, then $X_i \mid X_1, \ldots, X_{i-1}, Y \sim \mathcal{N}(\tilde{\mu}, \tilde{\sigma})$, where

$$\begin{split} \tilde{\mu} &= \mu_i + \Sigma_{[i,1:i-1]} \Sigma_{[1:i-1,1:i-1]}^{-1} (x_{[1:i-1]} - \mu_{[1:i-1]}) \\ \tilde{\sigma} &= \Sigma_{ii} - \Sigma_{[i,1:i-1]} \Sigma_{[1:i-1,1:i-1]}^{-1} \Sigma_{[1:i-1,i]}. \end{split}$$

Setting off-diagonal elements to be 0, we recover

$$P(X_i \mid X_{i-1}, \dots, X_1, Y) \sim \mathcal{N}(\mu_i, \Sigma_{ii}).$$

We can use the values of $\tilde{\mu}$ and $\tilde{\sigma}$ above to derive closed-form (albeit cumbersome) expressions for woe($Y=1:X_i\mid X_{i-1},\ldots,X_1$) in terms of log-density ratios of normal distributions. The total WoE is analogous to the total WoE for GNB. For example, LDA makes a homoscedasticity assumption ($\Sigma_1=\Sigma_0=\Sigma$), so the total WoE satisfies

$$woe(Y = 1 \mid X) > 0 \iff d_{\Sigma}^{2}(x, \mu_{1}) - d_{\Sigma}^{2}(x, \mu_{0}) < 0.$$

E. Use Cases and Limitations of WoE Explanations

In this section, we discuss how—and whether—to choose between post-hoc interpretability methods, focusing on how to choose between WoE explanations and other methods.

E.1. No Explanation is Inherently "Better"

In Section 2 we proposed a list of design principles that we distilled from the literature on the nature of explanation from philosophy, cognitive science, and the social sciences. However, distilling universal principles for what makes one explanation better than another is much more difficult. Indeed, the answer to this question is highly context dependent. This implies that explanations generated by different interpretability methods might be useful in different situations,

depending on the type of model, the data, the user, and the intended use of the explanations (Vaughan & Wallach, 2020).

Further complicating matters is the fact that post-hoc interpretability methods are, by definition, imperfect. Summarizing the behavior of complex models comes at a price (Rudin, 2019)—that is, the explanations are partial, only hold in a small neighborhood (Ribeiro et al., 2016) or make strong assumptions about the data (Lundberg & Lee, 2017). As a result, it is seldom the case that explanations generated by one interpretability method strictly dominate explanations generated by another: there are always be scenarios in which one method's assumptions and approximations will be more detrimental than another's. Furthermore, different explanations of the same prediction might reveal information about different aspects of the underlying model's behavior.

Based on this premise, we next discuss when WoE explanations are likely to be useful—as complements to or substitutes for other post-hoc interpretability methods—and when they are not. Our goal is to provide guidelines for deciding when to use our method and when to use other methods. We focus on LIME (Ribeiro et al., 2016) and SHAP (Lundberg & Lee, 2017) because these methods are very widely used.

E.2. When Are WoE Explanations Useful?

We first discuss three main settings in which there is a clear case for using explanations based on weight of evidence.

The underlying model is generative. Explaining the predictions made by a generative model in generative terms (c.f. Appendix C) seems, conceptually, a better fit than doing so in discriminative terms. But there are other tangible reasons to use WoE explanations for generative models too: First, generative models already compute conditional likelihoods "under the hood." Even these conditional likelihoods are not accessible (e.g., as is the case with black-box models), it is reasonable to think that they will be stable, as will be their empirical estimates, even for small sample sizes. Indeed, we showed in Section 4.1 that when the underlying model is generative, WoE values can be very accurately estimated.

The underlying model is log linear. If the underlying model is log linear or yields simple log-odds ratios, then the WoE might have a closed-form, or at least simple, expression. For example, for logistic regression, the log odds are linear, as we explained in Appendix D. This differs from post-hoc interpretability methods like LIME and SHAP, which need to be modified to accommodate non-linear link functions.

The underlying model is a multi-class classifier. In their original forms, both LIME and SHAP produce one-shot explanations in for the predicted class. When the number of classes is large, this is unlikely to yield useful explanations. The WoE, on the other hand, naturally extends to settings

where the hypotheses h and h' to contrast correspond to sets of classes, as discussed in Section 3.2. Indeed, in our user study, participants found that sequential explanations helped them to understand how each of the classes were ruled out.

Even in cases where the underlying model is not generative or log linear, it might still be desirable to explain its predictions in generative terms, perhaps as a complement to other post-hoc interpretability methods. However, WoE explanations should only be used if the following conditions hold.

Conditional likelihoods are accessible or can be accurately estimated from finite samples. As we explained in Section 3.3, the meta-algorithm for generating WoE explanations requires access to the conditional likelihoods $P(X_{\mathcal{A}_i}|X_{\mathcal{A}_{i-1}},\ldots,X_{\mathcal{A}_1},Y)$. If the model computes all necessary conditional likelihoods internally, then they can be used directly; however, in other cases, they must be estimated from samples. Our quantitative experiments in Section 4.1 suggest that the WoE can be accurately estimated—even in relatively high dimensions—from finite samples.

Log-odds ratios are meaningful units. Following Principle 4, explanations should rely on easily-understandable quantities. As we discussed in Section 3.1, there is ample evidence to suggest that the units in which the WoE is expressed (log-odds ratios) are easily understandable. However, we recommend experimentally verifying that this is the case in any scenario which WoE explanations are to be used.

F. Implementation Choices

In this section, we further describe how our method breaks up explanations of the predictions of complex multi-class classifiers into sequences of "smaller" explanations, and discuss the challenge of conditional likelihood estimation.

F.1. Class partitioning for sequential explanations

As we described in Section 3.2, there is flexibility in choosing the hypotheses h and h' to contrast. The obvious choice of letting h correspond to the predicted class y^* and h' its complement is unlikely to yield useful explanations when he number of classes is large. Following Principle 3 (modularity), our method addresses this by casting explanation as a sequential process, whereby a subset of the possible outcomes is ruled out at each step. By design, the other subset (i.e., the subset that is reserved) contains the predicted class y^* . In other words, with each subsequent step, a smaller set of classes is preserved until h consists of only y^* (see Figure 4 for an illustration). At the end of this sequential process, every alternative y' has been ruled out (c.f. Principle 2).

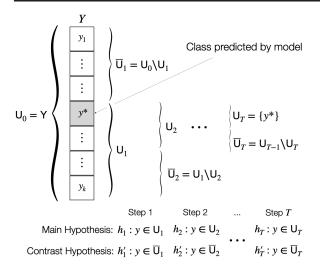


Figure 4. For complex multi-class classifiers, our our method breaks up explanations into sequences of "smaller" explanations.

F.2. Finite-Sample WoE Estimation

Our meta-algorithm requires access to the model's conditional likelihoods $P(X_{\mathcal{A}_i} \mid X_{\mathcal{A}_{i-1}}, \dots, X_{\mathcal{A}_1}, Y)$ to compute the per-atom WoE.4 In the best case, the model computes all necessary conditional likelihoods internally. However, if the model is a black box or does not compute likelihoods internally, then these must be estimated from samples. In some settings it might be feasible to fit a conditional likelihood estimation model as a preliminary offline step prior to running the meta-algorithm. For simpler data sets, this might be achieved via classic (e.g., kernel or spectral) density estimation methods. For more complex data sets, such as image data sets, methods based on normalizing flows and autoregressive models (e.g., Rezende & Mohamed, 2015; Papamakarios et al., 2017) are likely more appropriate. If fitting such a model is intractable, we can use a naïve Bayes (NB) approximation, fitting only the marginal likelihoods.

G. User Study in Further Detail

In this section, we further discuss our user study.

G.1. Tutorial

Kaur et al. (2020) found that practitioners misunderstand, over-trust, and misuse interpretability tools, highlighting the importance of providing documentation and tutorials to accompany them. For our study, we used an iterative process and pilot studies to design a tutorial to introduce the concepts and functionalities needed to use our tool. The tutorial was based on a Jupyter notebook (see Figures 5 and 6)

and contained equations, text, and images covering log-odds ratios, weight of evidence, feature groups, and sequential explanations. The tutorial took approximately forty minutes to complete and and contained checkpoint questions intended to provide insight into participants' understanding.

G.2. Main Study

The goal of the main study was to assess participants' understanding of the WoE and investigate their use of the tool in the context of a practical task. Participants were given a Jupyter notebook (see Figures 7–9) that included a dataset, an ML model trained using the dataset, and our interpretability tool. They were then asked to answer several questions.

The model was a random-forest classifier trained using the Online News Popularity dataset (Fernandes et al., 2015), which consists of 39,797 news articles. Each article is represented using 59 features that capture metadata about the article, such as its length, any links, and its sentiment polarity. We trained the model to predict the category that each article was published under (e.g., "Lifestyle" or "Business"), yielding a six-class classification task. We chose this dataset and this task because the domain is understandable without expert knowledge or prior experience, the number of classes is large enough to permit meaningful sequential explanations, and there are enough features to make explanations based on feature groups sufficiently different from explanations based on individual features.

The main study consisted of two parts, which were designed to let us observe the use of the two extensions of the WoE described in Section 3.2: feature groups and sequential explanations. In the first part, participants were given the option to view explanations based on feature groups or explanations based on individual features, and were asked questions that could be answered using either type of explanation (e.g., "Which aspects of the news article contributed the most to this prediction?"). This part of the study was intended to surface participants' preferences. In the second part, participants were given the option of generating one-shot or sequential explanations, but were asked questions that could only be answered precisely using sequential explanations (e.g., "Why didn't the model predict [subset of classes]?"). This part of the study was intended to assess whether participants could successfully use sequential explanations.

G.3. Participants

Potential participants were recruited via email and asked to complete a survey about their ML background and their experience with interpretability tools in order to be considered for the study. Of 41 survey respondents, we randomly selected 10 to participate in the study. All participants were ML practitioners with 1–20 years of experience. On average, participants rated the role of ML in their jobs as 6.7 and their

⁴We note that our meta-algorithm implicitly assumes an ordering of the atoms. This ordering might affect the WoE values.

experience with interpretability tools as 3.2, both on a scale of 0 ("not at all") to 7 ("extremely"). Participants also rated their familiarity with concepts from probability relevant to the WoE on a scale of 0 to 7. Their average ratings were 2.7 for posterior class probabilities, 3.3 for log likelihoods, 3.2 for log-odds ratios, and 0.9 for the WoE. On average, participants took 1.7 hours to complete the study. Each participant was compensated with a \$40 Amazon gift card.

H. Jupyter Notebooks

Below, we provide excerpts from the Jupyter notebooks that we used in the tutorial and in the main study. The complete notebooks are provided in the supplementary materials.

WoE UserStudy Tutorial

July 1, 2020

User Study on Interpretability - Tutorial

Thank you for participating in our study! The study is structured as follows

- 1. Tutorial: Overview of background concepts that will be used in the rest of the study.
- Setup Description: Presentation of the dataset used, descriptive statistics, e
- Main Component: Using the interpretability tool to answer questions about an ML model.
 Follow-Up: Questionnaire and interview.

Please keep this tutorial open and handy while you complete the study. You're welcome (and encouraged!) to refer back to it at any point.

Concepts covered in this tutorial

Weight of Evidence

- Definition
- Interpretation
- Binary vs. Multiclass
 Grouping Features
 Sequential Explanations
 Example

Weight Of Evidence



Interpreting WoE Scores

Regargless of which of the two formal interpretations we use, colloquially, using the language of the Weight of Evidence literature, we would say: * woe(Y = 1 : $X_{cough} = 1$) > 0 \Longrightarrow the presence of cough speaks in favor of this patient having the flu (Y = 1)

- woe $(Y = 1 : X_{\text{cough}} = 1) = 0$ patient having the flu (Y = 1)the presence of cough doesn't speak for nor against this
- $woe(Y = 1 : X_{cough} = 1) < 0$ \implies the presence of cough *speaks against* this patient having the flu (Y = 1)

But what does the magnitude of the WoE tell us about the strength of the evidence? This table provides

Odds Ratio (Interp. 1) = Proba.			
Weight of Evidence Score	Ratio (Interp. 2)	Strength of Evidence	
0 to 1.15	1 to 3	Not worth mentioning	
1.15 to 2.3	3 to 10	Substantial	
2.3 to 4.61	10 to 100	Strong	
> 4.61	> 100	Decisive	

Note: This same table, with negative values, can be used to quantify the evidence against the hypothesis Let's see a few concrete examples for our medical diagosis setting

$$\begin{aligned} & woe(Y=1:X_{lever}=1)=3 & \Longrightarrow & \text{having a fever provides strong evidence that the patient has the flu} \\ & woe(Y=1:X_{beadache}=1)=0.7 & \Longrightarrow & \text{having a headache provides some, but not much, evidence of a flu} \\ & woe(Y=1:X_{cough}=0)=-2 & \Longrightarrow & \text{not having a ough provides substantial evidence against having a} \\ & woe(Y=1:X_{natusea}=0)=0 & \Longrightarrow & \text{not having natuse a provides no evidence for nor against having a} \end{aligned}$$

WoE Scores are Additive

When considering multiple features (e.g., symptoms) simultaneously, individual WoE scores ${\bf can \ be \ added}$ to obtain a combined total WoE score. For example, if $X_{\rm cough}$ and $X_{\rm fever}$ are independent, then:

$$woe(Y=1:X_{cough}=1,X_{fever}=0) \hspace{0.2cm} = \hspace{0.2cm} woe(Y=1:X_{cough}=1) \hspace{0.2cm} + \hspace{0.2cm} woe(Y=1:X_{fever}=0)$$

For ML classifiers, this will allow us to break down a prediction (related to the left-hand side) into individual feature contributions (right-hand side).

Checkpoint Questions

Suppose X_{cough} , X_{nausea} , X_{chills} are independent. If for a given patient, we have:

- Fact 1:
- $woe(Y = 1 : X_{cough} = 0) = -1$ $woe(Y = 1 : X_{nausea} = 1) = 0$ $woe(Y = 1 : X_{chills} = 1) = 3.3$ • Fact 3:

Q1: How would you interpret these facts? You can use either of the two interpretations (odds or probabil-

Setup

The study will focus on machine learning classifiers, so we will introduce the Weight of Evidence using a (made up) classification example.

Suppose we are trying to predict the variable Y, where:

- Y = 1: the patient has the flu
 Y = 0: the patient does not have the flu

based on binary indicators X of symptoms (e.g., $X_{cough} = 1$ if the person has a cough, and 0 otherwise).

Throughout this section we will use "being sick" and "having the flu" interchangeably for Y=1, and "being healthy" and "not having the flu" for Y=0.

Disclaimer: any specific values (probabilities, etc.) provided here are entirely fabricated for illustration

Definition

The Weight of Evidence (WoE for short), is a concept used to quantify feature importance, and it attempts

"does the evidence speak in favor or against a certain hypothesis?"

In this study we are interested in 'explaining' predictions of ML classifiers, so the 'evidence' will be some of the input features (e.g., symptoms), the 'hypothesis' will usually be the model's prediction (e.g., Y='sick') and the question we seek to answer is:

"according to the model, how much does the input speak in favor of a certain prediction"

As an example, suppose we want to understand how having a cough (i.e, $X_{\text{cough}} = 1$) affects the probability (according to the classifier) of having the flu (i.e., Y = 1). The Weight-of-Evidence of $X_{\text{cough}} = 1$ towards Y = 1 is:

$$\mathsf{woe}(\mathit{Y}=1:\mathit{X}_{\mathsf{cough}}=1) \quad \overset{\mathsf{def.}}{=} ^{1} \quad \log \frac{\mathsf{Odds}(\mathit{Y}=1 \mid \mathit{X}_{\mathsf{cough}}=1)}{\mathsf{Odds}(\mathit{Y}=1)}$$

Conveniently for those who find probabilities more intuitive than odds, the WoE has a (mathematically equivalent) alternative definition:

$$\label{eq:woe} \text{woe}(Y=1:X_{\text{cough}}=1) \quad \overset{\text{def. 2}}{=} \quad \log \frac{P(X_{\text{cough}}=1 \mid Y=1)}{P(X_{\text{cough}}=1 \mid Y=0)}$$

which uses probabilities instead of odds, and is 'reverted' in the sense that it quantifies the change in probability of the evidence X instead of the outcome Y.

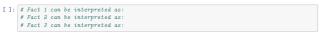
These equivalent definitions lead to two alternative interpretations. For our example above, suppose

$$woe(Y=1:X_{cough}=1)=\log 2\approx 0.30$$

for some patient. This can be interpreted as:

- Odds Interpretation: "The posterior odds of having the flu double after taking into account the cough (compared to the prior odds of having it)"
- $\bullet \ \, \textbf{Likelihood Interpretation:} \ \text{``A person is twice as likely to } \textit{have a cough} \ \text{if they have the flu, compared} \\$ to when they are healthy'

To simplify things, from now on we will simply show woe scores as real numbers $\in (-\infty,\infty)$ (e.g., 0.30 for the example above) but will provide guidelines on how to convert/interpret them below.



Q2: What is the total weight-of-evidence of these symptoms toward this patient having the flu? How would you interpret this?

Please check in with the researchers when you get to this point.

Binary vs. Multiclass

Since Y is binary in our example so far, there's only two possible hypotheses:

Y = 1: the patient has the flu (let's say this is the 'primary hypothesis') or
 Y = 0: the patient does not have the flu (the 'alternative hypothesis').

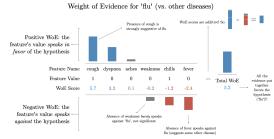
Since there are only two hypotheses, evidence against one of these is evidence in favor of the other.

But what if this were multi-class classification instead? E.g., suppose the model must instead predict one of K possible conditions, and that for a given patient the model predicts Y='flu', which we take as the primary hypothesis. The alternative hypothesis h' could be:

- All the other possible diseases, e.g., h': Y ∈ {cold', 'strep', 'allergies',...}
 Another specific disease, e.g., h': Y = 'cold'
 Any other subset of diseases, e.g., 'viral' or 'bacterial'

Each of these might shed light on different aspects of the prediction. We will always indicate clearly what h and h' are for a specific instance.

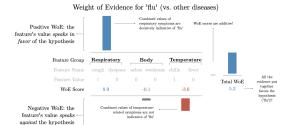
For our running example, taking Y = 'flu' and Y = 'any other disease except flu' as primary/alternate hypothesis, a possible WoE decomposition would be:



WoE of Individual Features and Feature Groups

In the plot above, we showed the WoE score of each feature. But when the number of features is large, and there is a meaningful way to group them, it is often convenient to show WoE scores aggregated by group of features

For our running example, a sensible grouping of the six symptoms would be: *'respiratory' (cough, dispnea) * overall 'body' feeling (aches, weakness) * 'temperature' (chills, fever). In that case, we could instead display:



which might let us quickly realize that the most decisive factors supporting this prediction are respiratory.

Sequential Explanations

So far we have shown 'one-shot' explanations: the WoE of the predicted class against all other classes. But when there's multiple classes, it is sometimes useful to **break down** the explanation into various 'steps'. For our diagnosis example, suppose the model predicts 'flu'. It might be illustrative to understand:

- 1. What evidence points to *viral diseases* ('flu', 'avian flu', etc.) instead of *bacterial* ones ('strep', etc).

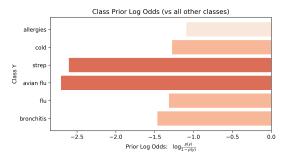
 2. What evidence singles out common 'flu' over other viral diseases.

For this purpose, we can use the Weight of Evidence iteratively with increasingly refined hypotheses: First, we produce an explanation for why the model would predict 'viral' instead of 'bacterial':

Therefore, adding up all the WoE scores plus the log priors, we obtain posterior log-odds, which are directly related the model's predictions.

A Word of Caution. Note that it could be that all classes have negative prior log-odds. This just means all classes have prior probability < 0.5, which is common in multi-class classification. What matters here is the relative order of these prior odds.

Consider this example:



From this plot, we can say:

- Although both have negative prior log-odds, the ones for Y = 'strep' are much lower (more negative) that those of Y = 'allergies' (i.e., 'strep' is significantly less likely a priori than 'allergies').
 Even moderately strong evidence favoring Y = 'allergies' might be enough to tip the prediction
- The evidence would have to be much stronger for the model to predict Y = 'strep' because it has to overcome very unfavorable prior odds.

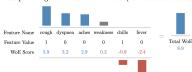
A Real Example

Consider the following example. A patient has fever, no cough, and no other symptoms, i.e.,

$$X_{\text{fever}} = 1$$
, $X_{\text{cough}} = 0$, and $X_i = 0$ for every other symptom

and the machine learning classifier predicts Y = 'flu'. Again, we assume the symptoms are independent. The following is an actual plot produced by our WoE-Explainer tool for this example:

Step 1: Weight of Evidence for 'viral' (vs. 'bacterial' diseases)



Note that the total WoE does indeed favor 'viral', which is expected since the model's prediction ('flu') falls

Next, we produce an explanation for why the model predicted 'flu' an not any other label in the 'viral' class:

Step 2: Weight of Evidence for 'flu' (vs. other 'viral' diseases)



Of course, we could group the diseases in some other way (e.g., severe vs. mild, contagious vs. non-contagious, etc), leading to different WoE sequences.

Prior and Posterior Probabilities

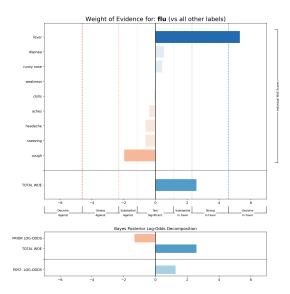
In order to understand how the WoE influences a model's prediction, we need one more key component: the prior class probabilities.

Intuitively, if the prior (i.e., marginal) probability for a certain class is low (e.g., because the training data was very unbalanced), then the *evidence* in favor of it would have to quite strong in order for the model to predict it (over more frequently occurring labels).

Fortunately, the WoE has another property that formalizes this very intuition, and it's given by the identity:

Posterior log-odds = Prior log-odds + Weight of Evidence

$$\log \frac{P(Y = '\text{flu'} \mid X_{\text{Cough}}, X_{\text{fever}}, \dots)}{P(Y \neq '\text{flu'} \mid X_{\text{Cough}}, X_{\text{fever}}, \dots)} \\ = \underbrace{\log \frac{P(Y = '\text{flu'})}{P(Y \neq '\text{flu'})}}_{\text{Prior log-odds}} + \underbrace{\log \frac{P(X_{\text{Cough}} \mid Y = '\text{flu'})}{P(X_{\text{Cough}} \mid Y \neq '\text{flu'})}}_{\text{Weight of evalence sores}} + \underbrace{\log \frac{P(X_{\text{Four}}, X_{\text{flur}})}{P(X_{\text{Cough}} \mid Y \neq '\text{flu'})}}_{\text{Weight of evalence sores}} + \underbrace{\log \frac{P(X_{\text{Four}}, X_{\text{flur}})}{P(X_{\text{Cough}} \mid Y \neq '\text{flu'})}}_{\text{Weight of evalence sores}} + \underbrace{\log \frac{P(X_{\text{Four}}, X_{\text{flur}})}{P(X_{\text{Cough}} \mid Y \neq '\text{flu'})}}_{\text{Weight of evalence sores}} + \underbrace{\log \frac{P(X_{\text{Four}}, X_{\text{flur}})}{P(X_{\text{Cough}} \mid Y \neq '\text{flu'})}}_{\text{Weight of evalence sores}} + \underbrace{\log \frac{P(X_{\text{Four}}, X_{\text{flur}})}{P(X_{\text{Cough}} \mid Y \neq '\text{flur'})}}_{\text{Weight of evalence sores}} + \underbrace{\log \frac{P(X_{\text{Four}}, X_{\text{flur}})}{P(X_{\text{Cough}} \mid Y \neq '\text{flur'})}}_{\text{Weight of evalence sores}} + \underbrace{\log \frac{P(X_{\text{Four}}, X_{\text{flur}})}{P(X_{\text{Four}}, X_{\text{flur}})}}_{\text{Weight of evalence sores}} + \underbrace{\log \frac{P(X_{\text{Four}}, X_{\text{flur}})}_{\text{flur}}}_{\text{flur}}}_{\text{flur}} + \underbrace{\log \frac{P(X_{\text{Four}}, X_{\text{flur}})}_{\text{flur}}}_{\text{flur}}}_{\text{flur}}}_{\text{flur}}}_{\text{flur}}_{\text{flur}}_{\text{flur}}}_{\text{flur}}}_{\text{flur}}$$



Note that:

- . The features are now displayed vertically (instead of horizontally), but the meaning and interpretation remains the same as before
- As before, blue and red bars denote positive and negative weight-of-evidence, respectively. The shade of the bars encodes the degree significance of WoE according to the table above.

Checkpoint Questions

Based on the WoE explanation above, please answer the following questions:

Q3: According to this classifier, does having a fever increase or decrease the odds of having a flu for this person? What about a having a cough?

Answer:

Figure 6. Jupyter notebook for the tutorial (continued).

WoE User Study

February 9, 2021

1 User Study on Interpretability - Main Sections

BEFORE YOU BEGIN:

- Make sure this is running on the Python 3.6 Kernel (not Python 3). This can be changed in the 'Kernel' menu above.
- Go to "Cell" -> "Run All" to start executing preliminary commands in the background while you read the instructions below.

1.0.1 Description:

Throughout this study we will be using the 'Online News Popularity' dataset.

Each instance in this dataset is a news article published in mashable.com, characterized by 53 features describing its length, contents, polarity and some metadata. We will provide short descriptions of each feature below. The data consists of 33,510 examples (80%/20% training/testing).

The task is to predict the *channel* ('world', 'tech', 'entertainment', 'business', 'social media' or 'lifestyle') in which each news article was published.

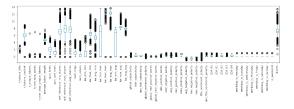
The 'Preliminaries' section below is a typical ML pipeline: data loading, description, model training and evaluation.

[for i,idxs in enumerate(feature_groups.idxs): print('\nFeatue Group {\cdot\}: {\cdot\}'.format(i, feature_groups.idxs):

After the model is trained, the interpretabilty tool will be instantatied and used to explain the predictions of this model.

1.0.2 Instructions:

- Please read carefully and execute all cells (if you did "Run All", the first part will already
 be executed, no need to run those again).
- At the end of each section you will find a some questions, which you can answer in the empty cells provided below them.
- If you have any questions, please let the researcher now.
- Feel free to refer to the tutorial if you need a reminder of any of the concepts introduced there.



Note that the integer-valued features have been scaled (by taking log).

Model Training We will train a classifier on this data.

1.2 PART 1

Insantiate Explainers We now create a Weight of Evidence estimator, and an explainer wrapper around it.

```
7]: import importlib
from src.utils import range_plot
from src.explainers import WOE_Explainer
from src.woe import woe_gaussian

woe_estimator = woe_gaussian(classifier, X.train, classes = range(len(Y.
__names)), cond_type='nb')
```

1.1 Preliminaries: Data, Features, Meta-Features & Models

```
inport sys
import importlib
import numpy as np
import sklearn
import pandas as pd
import matplotlib.pyplot as plt
sys.path.append('../')
```

The target variable is the 'channel', which has 6 classes, not evenly distributed:

Class	Examples	
world	8427	
tech	7346	
entertainment	7057	
business	6258	
socmed	2323	
lifestyle	2099	
Name: channel	dt.vpe:	int.6

This dataset has 53 features, which could be hard to analyze simultaenously. Fortunately, there's many variables that encode similar aspects of the input, like length or polarity. A faily simple and natural grouping of features is shown below.

Note: there is no need to read the description of all features. Should you need them, you can scroll back here and read those that might be relevant for questions later on.

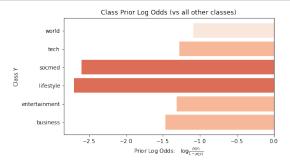
```
3]: for i,idxs in enumerate(feature_groups.idxs):
    print('\nFeatue Group (): ()'.format(i, feature_groups.names[i].upper()))
    for j in idxs:
        print(' {:30}\t->\t{\}'.format(X.names[j], feature_desc[X.names[j]]))
```

```
eatue Group 0: LENGTH
   n tokens title
                                                Number of words in the title
   n_tokens_content
                                                Number of words in the content
                                       ->
   n unique tokens
                                                Rate of unique words in the
content
   n non stop words
                                                Rate of non-stop words in the
content
   n_non_stop_unique_tokens
                                               Rate of unique non-stop words in
the content
   average token length
                                                Average length of the words in
```

```
total_woe_correction=True,
  classes=Y.names, features=X.names,
  X=X.train, Y=Y.train,
  featgroup_idxs = feature_groups.idxs,
  featgroup_names = feature_groups.names)
```

Before explaining specific examples, let's look at the model's prior class probabilities.

```
8]: fig, ax = plt.subplots(1,1, figsize=(7,4))
weexplainer.plot_priors(normalize = None, ax = ax)
plt.show()
```



As discussed in the tutorial, lower prior log odds require stronger evidence to overcome them. In this case, 'social media' and 'lifestyle' have much lower prior log odds that the other classes (because the data is unbalanced!).

Let's pick an example from the test set:

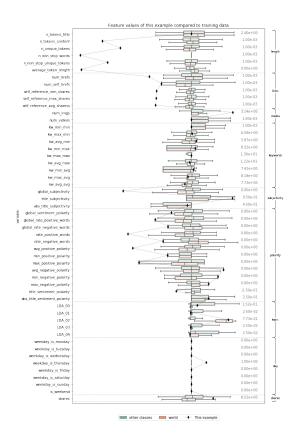
```
9]: idx_1 = 4 # Don't change this
x_1 = X.test[idx_1].reshape(1,-1)
y_1 = Y.test[idx_1].reshape(1,)
```

The first set of questions on this section will be based on this example.

Let's see what the model predicts:

```
0]: pred_class = classifier.predict(x_1)[0]
```

Figure 7. Jupyter notebook for the main study (some output pages omitted for brevity).



The boxplots have been centered and scaled in this plot to facilitate visualization.

While the actual values of the features are not too important, the position of the black dots (the example being explained) with respect to the training is useful to understand how this instance relates other examples.

Now we explain the model's prediction for this example, using the Explainer tool.

Attention: Here, you have to choose whether to visualize the explanation by features of by feature groups. Don't worry! You can switch as needed.

```
2]: ### Uncomment one to select TYPE of emplanation unit

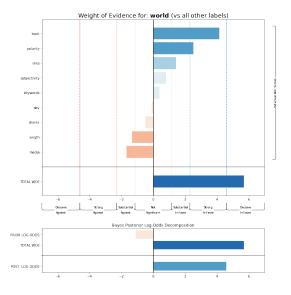
#emplanation_units = 'features'
explanation_units = 'featuregroups'

e = woeexplainer.explain(x_1,y_1, totext=False, units=explanation_units)

Prediction: 'world' (p=0.99)
True Class: 'world'
Primary Hyp. (in favor of): 'world'
Altern. Hyp. (against):
'business', 'entertainment', 'lifestyle', 'socmed', 'tech'
Bayes Odds Decomposition:

4.60 = -1.09 + 5.69
post. log-odds = prior log-odds + total_woe

Total WoE in favor of 'world': 5.69
```



If you want to look at the feature boxplots for this example, uncomment the following

As before, you can **select** how to display the explanation:
71: ### Uncomment one to select TYPE of explanation unit

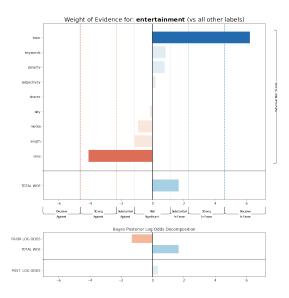
Q1: In plain English, what would you say are main characteristics of this news article that the model is relying on to make its prediction? Answer:

```
3]: # The prediction is mostly based on these chacterteristics:
# 1. The article ...
# 2. The article ...
# 3. The article ...
```

Let's clear the variables before moving on:

```
4]: if 'idx_1' in globals(): del idx_1
    if 'explanation_units' in globals(): del explanation_units
```

Figure 8. Jupyter notebook for the main study (continued).

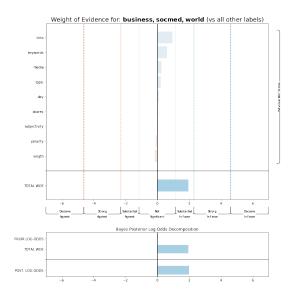


 $\mathbf{Q2}\text{:}\ \, \text{The model}$ is not very confident about its prediction. Why do you think that is? Answer:

```
8]: # This prediction is not very confident because ....
```

Q3: In plain English, how would you modify this article to make the model more confident of its prediction, while not changing the article 'too much'? Answer:

```
9]: # I would change ...
```



```
Explanation Step: 2
Prediction: 'business' (p=0.75)
True Class: 'business'
Primary Hyp. (in favor of): 'business','socmed'
Altern. Hyp. (against): 'world'
Bayes Odds Decomposition:

3.76 = 0.02 + 3.74
post. log-odds = prior log-odds + total_woe

Total WoE in favor of 'business','socmed' (against 'world'): 3.74
```

1.3 Part

For the second part of the study, we will continue working with the same dataset and model, but will now try to answer a different set of questions.

Let's pick another example:

```
10]: idx_3 = 55 # Don't change this.
x_3 = X.test[idx_3].reshape(1,-1)
y_3 = Y.test[idx_3].reshape(1,)
```

If you want to look at the feature boxplots for this example, uncomment the following:

Let's see what the model predicts in this case:

```
[2]: pred_class = classifier.predict(x_3)[0]
pred_proba = classifier.predict_proba(x_3)[0][pred_class]
print(f"Predicted class: {Y.names[pred_class]} (prob: {pred_proba})")
print(f"True class: {Y.names[y_3.squeeze()]}")
```

Predicted class: business (prob: 0.75)
True class: business

'entertainment', 'lifestyle', 'tech'):

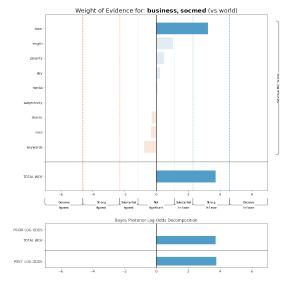
Tao crabb. Dabinobb

Let's explain it. Now, **you must choose** whether to produce a **sequential** or **one-shot** explanation. Again, feel free to change between these as needed.

```
Explanation Step: 1
Prediction: 'business' (p=0.75)
True Class: 'business' (p=0.75)
True Class: 'business' (p=0.75)
Altern. Hyp. (in favor of): 'business', 'socmed', 'world'
Altern. Hyp. (against): 'entertainment', 'lifestyle', 'tech'
Bayes Odds Decomposition:

1.99 = 0.03 + 1.96
post. log-odds = prior log-odds + total_woe

Total WoE in favor of 'business', 'socmed', 'world' (against
```



1.96

```
Explanation Step: 3
Prediction: 'business' (p=0.75)
True Class: 'business'
Primary Hyp. (in favor of): 'business'
Altern. Hyp. (against): 'socmed'
Bayes Odds Decomposition:

1.92 = 1.00 + 0.92
post. log-odds = prior log-odds + total_woe

Total WoE in favor of 'business' (against 'socmed'): 0.92
```

Figure 9. Jupyter notebook for the main study (continued).