

Anchors: High-Precision Model-Agnostic Explanations

Marco Tulio Ribeiro
University of Washington
marcotcr@cs.washington.edu

Sameer Singh
University of California, Irvine
sameer@uci.edu

Carlos Guestrin
University of Washington
guestrin@cs.washington.edu

Abstract

We introduce a novel model-agnostic system that explains the behavior of complex models with high-precision rules called *anchors*, representing local, “sufficient” conditions for predictions. We propose an algorithm to efficiently compute these explanations for any black-box model with high-probability guarantees. We demonstrate the flexibility of anchors by explaining a myriad of different models for different domains and tasks. In a user study, we show that anchors enable users to predict how a model would behave on unseen instances with less effort and higher precision, as compared to existing linear explanations or no explanations.

Introduction

Sophisticated machine learning models such as deep neural networks have been shown to be highly accurate for many applications, even though their complexity virtually makes them black-boxes. As a consequence of the need for users to understand the behavior of these models, *interpretable machine learning* has seen a resurgence in recent years, ranging from the design of novel *globally*-interpretable machine learning models (Lakkaraju, Bach, and Leskovec 2016; Ustun and Rudin 2015; Wang and Rudin 2015) to local explanations (for individual predictions) that can be computed for any classifier (Baehrens et al. 2010; Ribeiro, Singh, and Guestrin 2016b; Strumbelj and Kononenko 2010).

A question at the core of interpretability is whether humans understand a model enough to make accurate predictions about its behavior on unseen instances. For instances where humans can confidently predict the behavior of a model, let (human) *precision* be the fraction in which they are correct (note that this is human precision, not model precision). High human precision is paramount for real interpretability - one can hardly say they understand a model if they consistently think they know what it will do, but are often mistaken.

Most local approaches provide explanations that describe the local behavior of the model using a linearly weighted combination of the input features (Baehrens et al. 2010; Ribeiro, Singh, and Guestrin 2016b; Strumbelj and Kononenko 2010). Linear functions can capture relative importance of features in an easy-to-understand manner. However, since these linear

+ This movie is not bad. - This movie is not very good.

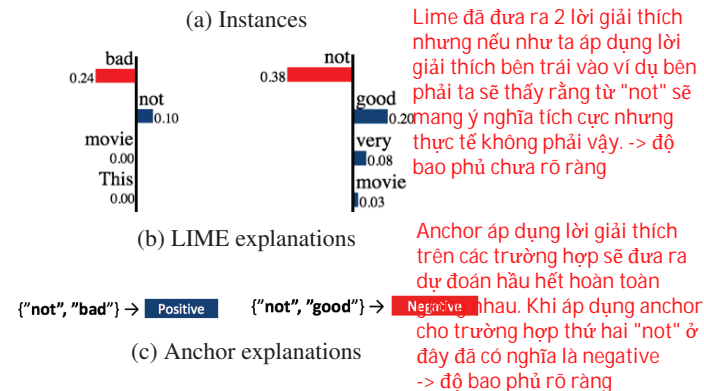


Figure 1: Sentiment predictions, LSTM

Hầu hết các phương pháp giải thích hành vi cục bộ là sử dụng tổ hợp trọng số tuyến tính các đặc trưng đầu vào -> hiểu được các sự liên quan quan trọng của các đặc trưng một cách dễ hiểu -> nhưng độ bao phủ của nó chưa rõ ràng, nghĩa là không áp dụng được cho một vài trường hợp.

explanations are in some way local, it is not clear whether they *apply* to an unseen instance. In other words, their coverage (region where explanation applies) is unclear. **Unclear coverage can lead to low human precision, as users may think an insight from an explanation applies to unseen instances even when it does not.** When combined with the arithmetic involved in computing the contribution of the features in linear explanations, the human effort required can be quite high.

Take for example LIME (Ribeiro, Singh, and Guestrin 2016b) explanations for two sentiment predictions made by an LSTM in Figure 1. Although both explanations are computed to be *locally accurate*, if one took the explanation on the left and tried to apply it to the sentence on the right, one might be tempted to think that the word “not” would have a positive influence, which it does not. While such explanations provide insight into the model, their coverage is not clear, e.g. when does “not” have a positive influence on sentiment?

In this paper, we introduce novel model-agnostic explanations based on if-then rules, which we call *anchors*. An anchor explanation is a rule that sufficiently “anchors” the prediction locally – such that changes to the rest of the feature values of the instance do not matter. In other words, for instances on which the anchor holds, the prediction is (almost) always the same. For example, the anchors in Figure 1c state that the presence of the words “not bad” virtually guarantee a prediction of positive sentiment (and “not good” of negative

Anchor không phụ thuộc vào mô hình chỉ phụ thuộc vào quy tắc if-then -> lời giải thích của anchor luôn gắn chặt với giải thích cục bộ vì thế khi bạn có những thay đổi với phần còn lại của các giá trị đặc trưng của trường hợp thì cũng không quan trọng.

Anchor rõ ràng và dễ nắm bắt, và có độ bao phủ rất rõ ràng.

Trường hợp phóng to khu vực của các mô hình phức tạp. Lime sử dụng đường tốt nhất để phân biệt, phù hợp với mô hình dưới tập hợp D. -> không cho thấy biểu hiện của sự vững chắc vì đường giải thích của lime nằm trong hai miền giá trị nhưng anchor lại cho thấy lòng tin vững chắc hơn khi có sự rõ ràng, cửa sổ bao phủ nằm gọn trong một miền giá trị.

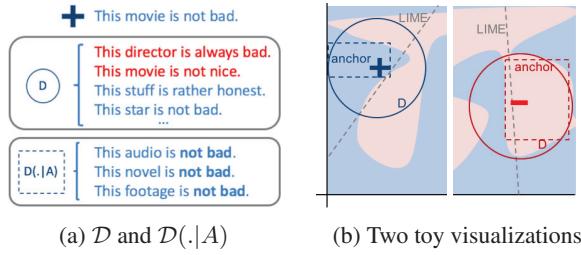


Figure 2: Concrete example of \mathcal{D} in (a) and intuition (b)

sentiment). Anchors are intuitive, easy to comprehend, and have extremely clear coverage – they only apply when all the conditions in the rule are met, and if they apply the precision is high (by design).

We demonstrate the usefulness of anchors by applying them to a variety of machine learning tasks (classification, structured prediction, text generation) on a diverse set of domains (tabular, text, and images). We also run a user study, where we observe that anchors enable users to predict how a model would **behave on unseen instances with much less effort and higher precision** as compared to existing techniques for model-agnostic explanation, or no explanations.

Anchors as High-Precision Explanations

Given a black box model $f : X \rightarrow Y$ and an instance $x \in X$, the goal of local model-agnostic interpretability (Ribeiro, Singh, and Guestrin 2016a; 2016b; Strumbelj and Kononenko 2010) is to explain the behavior of $f(x)$ to a user, where $f(x)$ is the individual prediction for instance x . The assumption is that while the model is globally too complex to be explained succinctly, “**zooming in**” on individual predictions makes the explanation task feasible. Most model-agnostic methods work by perturbing the instance x according to some “**perturbation distribution**” \mathcal{D}_x (for simplicity, \mathcal{D} from now on). In Ribeiro, Singh, and Guestrin (2016b), we emphasize that the perturbations \mathcal{D} (and explanations) must use an interpretable representation (i.e. one that makes sense to humans), even if the model uses an alternative representation of the input.

Let A be a rule (set of predicates) acting on such an interpretable representation, such that **$A(x)$ returns 1 if all its feature predicates are true for instance x** . For example, in Figure 2a (top), $x = \text{“This movie is not bad.”}$, $f(x) = \text{Positive}$, $A(x) = 1$ where $A = \{\text{“not”, “bad”}\}$. Let $\mathcal{D}(\cdot|A)$ denote the conditional distribution when the rule A applies (e.g. similar texts where “not” and “bad” are present, Figure 2a bottom). A is an *anchor* if $A(x) = 1$ and A is a sufficient condition for $f(x)$ with high probability — in our running example, if a sample z from $\mathcal{D}(z|A)$ is likely predicted as *Positive* (i.e. $f(x) = f(z)$). Formally A is an anchor if,

$$\mathbb{E}_{\mathcal{D}(z|A)}[\mathbb{1}_{f(x)=f(z)}] \geq \tau, A(x) = 1. \quad (1)$$

Figure 2b shows two “zoomed in” regions of a complex model, with particular instances (+ and -) being explained. LIME (Ribeiro, Singh, and Guestrin 2016b) explanations work by learning the lines that best approximate the model under \mathcal{D} , with some local weighting. The resulting expla-

| Instance | If | Predict |
|--------------------------------|-----------------------------|---------------|
| I want to play(V) ball. | previous word is PARTICLE | play is VERB. |
| I went to a play(N) yesterday. | previous word is DETERMINER | play is NOUN. |
| I play(V) ball on Mondays. | previous word is PRONOUN | play is VERB. |

Table 1: Anchors for Part-of-Speech tag for the word “play”

nations give no indication of how faithful they are (the explanation on the right is a much better local approximation of the black box model than the one on the left), or what their “local region” is. In contrast, even though they use the same \mathcal{D} , anchors are by construction faithful, adapting their coverage to the model’s behavior (the anchor on the right of Figure 2b is broader) and making their boundaries clear.

Leaving the discussion of how to compute anchors for later, we now demonstrate their usefulness and flexibility via concrete examples in a variety of domains and models.

Text Classification: We have already alluded to Figure 1, where we trained an LSTM model with paraphrastic sentence embeddings (Wieting et al. 2015) to predict the sentiment of reviews. In this case, the *features* used by the model are uninterpretable. The interpretable representation we use is the presence of individual tokens (words) in the instance. The perturbation distribution \mathcal{D} replaces “absent” tokens by random words with the same POS tag with probability proportional to their similarity in an embedding space (Pennington, Socher, and Manning 2014) (i.e. the generated sentences are coherent, and of the same length). We show samples from \mathcal{D} for a sentence in Figure 2a. **The anchor $A = \{\text{“not”, “bad”}\}$ is easy to apply: if the words “not” and “bad” are in the sentence, the model will predict “positive” with probability at least τ (set to 0.95 from here onwards). If either word (or both) are not present, we know we do not have sufficient information to know what the model will do.** Examples from $\mathcal{D}(z|A)$ are shown in Figure 2a (bottom).

Structured prediction: When the output of the algorithm is a structure, the anchor approach can be used to explain any function of the output. Anchors are particularly suited for structured prediction models: while the global behavior is too complex to be captured by simple interpretable models, the **local behavior can usually be represented using short rules.**

In Table 1, we explain the predictions of a state of the art part-of-speech tagger for the word “play” in different contexts, where we include the tags for neighboring words as part of the interpretable representation. The anchors demonstrate that the model is picking up on reasonable patterns of the English language, e.g. if play is preceded by a determiner, it is likely used as a noun.

In Table 2, we compute anchors for a multi-layer RNN encoder/attention-based decoder translation system (Vinyals et al. 2015) trained on English-Portuguese parallel corpora. In this case, anchors explain the presence of a word (or certain words) in the translation. The anchors (in bold) are computed with respect to the presence of the words in pink in the Por-

A là tập hợp các mệnh đề đặc trưng và $A(x) = 1$ nếu các mệnh đề đặc trưng đều đúng cho trường hợp x . nghĩa là {“not”, “bad”} tồn tại trong trường hợp x .
 \mathcal{D} là tập hợp các mệnh đề nhiễu loạn, gần đúng so với mệnh đề đã biết, thay thế các từ chưa dc thấy (“absent” token) bằng cách random từ với sự giống nhau từ POS tag và sự giống nhau phần trăm giống nhau trong không gian nhúng.
 $\mathcal{D}(\cdot|A)$ là tập hợp các mệnh đề nhiễu loạn có các mệnh đề đặc trưng của A , nghĩa là tồn tại {“not”, “bad”}
 $\mathcal{D}(z|A)$ là lấy một mệnh đề của tập $\mathcal{D}(\cdot|A)$, có thể xem là trường hợp z .
 A được xem là Anchor nếu $A(x) = 1$ và A là điều kiện đủ cho $f(x)$ với xác suất cao. nghĩa là tồn tại một mẫu z có $f(x) = f(z)$ có độ chính xác cao hơn τ . nghĩa là z phải có đủ tất cả các mệnh đề của A .

| English | Portuguese |
|---|--|
| This is the question we must address | Esta é a questão que temos que enfrentar |
| This is the problem we must address | Este é o problema que temos que enfrentar |
| This is what we must address | É isso que temos de enfrentar |

Table 2: Anchors (in bold) of a machine translation system for the Portuguese word for “This” (in pink).

| | If | Predict |
|----------------|---|----------------|
| adult | No capital gain or loss, never married | $\leq 50K$ |
| | Country is US, married, work hours > 45 | $> 50K$ |
| rcdv | No priors, no prison violations and crime not against property | Not rearrested |
| | Male, black, 1 to 5 priors, not married, and crime not against property | Re-arrested |
| lending | FICO score ≤ 649 | Bad Loan |
| | $649 \leq \text{FICO score} \leq 699$ and $\$5,400 \leq \text{loan amount} \leq \$10,000$ | Good Loan |

Table 3: Generated anchors for Tabular datasets

tuguese text. The first row in Table 2 means that when the words “This”, “is”, and “question” appear in English, the translation will include the word “Esta”. In Portuguese, the translation for the word “this” depends on the gender of the word it refers to (“esta” for feminine, “este” for masculine), or should be “isso” if its referent is not in the sentence. The anchors show that the model is capturing this behavior as it always includes “this is”, and the word that “this” refers to (“question” is feminine, “problem” is masculine).

Tabular Classification: Classification of data in tabular form (categorical and/or continuous features) is a popular application of machine learning. We use a validation dataset to define \mathcal{D} , and sample from $\mathcal{D}(z|A)$ by fixing the predicates in A and sampling the rest of the row as a whole. We show anchors for a few predictions of 400 gradient boosted trees trained on balanced versions of three datasets in Table 3. The anchors provide valuable insight into these models. Marital status appears in many different anchors for predicting whether a person makes $> \$50K$ annually (*adult* dataset). The anchors for predicting recidivism for individuals released from prison (Schmidt and Witte 1988) (*rcdv* dataset), show that this model is unfair if used for bail decisions, as race and gender feature prominently. For predicting whether a loan on the Lending Club website will turn out bad, i.e. late payment or default (*lending* dataset), the FICO score is sufficient in the extremes, but loan amount is taken into consideration otherwise. **We note that these are not exhaustive – the models are complex, and these anchors explain their behavior on part of the input space but not all of it. Anchors for “hard” predictions (in particular boundary cases) may be longer.**

Image Classification: When explaining the label prediction for an image we follow Ribeiro, Singh, and Guestrin (2016b),

segmenting the image into superpixels (Vedaldi and Soatto 2008) and using the presence or absence of these superpixels as the interpretable representation. In contrast to Ribeiro, Singh, and Guestrin (2016b), instead of *hiding* superpixels, we define $\mathcal{D}(z|A)$ by fixing the superpixels in A to the original image and superimposing another image over the rest of the superpixels. We explain a prediction of the Inception-V3 neural network (Szegedy et al. 2015) in Figure 3b. Even though \mathcal{D} is quite unrealistic here, the anchor demonstrates that the model focuses on various parts of the dog to determine its breed. An inspection of the (admittedly bizarre) images from $\mathcal{D}(z|A)$ in Figure 3c for which the model predicts “beagle” with high confidence illustrates that attributes that humans would consider essential for a beagle prediction (legs, not being underwater, not being in the sky, not having a human body) are not quite as essential to the neural network.

Visual Question Answering (VQA): As a final example, we present anchors for the VQA task: answering a question asked of a reference image. Here, we are interested in identifying which part of the *question* led to the predicted answer, and thus use the same representation and distribution as in Figure 2b. We explain predictions from the Visual7W open-ended VQA system (Zhu et al. 2016) using Figure 3a as the reference image. In Figure 3d we show a question/prediction pair and its anchor (in bold), as well as samples from $\mathcal{D}(z|A)$ and their predictions. The short anchor (“What”) reveals that, for this image, the model’s answer to many questions will be “dog”, contrary to our expectations. In Figure 3e, we show other question/answer pairs and their anchors, providing examples where the behavior of the classifier is aligned with our intuitions (first three) and where it is not (last question).

Related Work

Even in the few cases where having some understanding of a machine learning model’s behavior is not a requirement, it is certainly an advantage. Relying only on validation accuracy has many well studied problems, as practitioners consistently overestimate their model’s accuracy (Patel et al. 2008), propagate feedback loops (Sculley et al. 2015), or fail to notice data leaks (Kaufman, Rosset, and Perlich 2011).

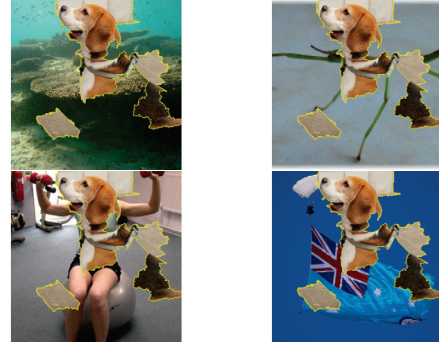
Compared to other interpretable options, rules fare well; users prefer, trust and understand rules better than alternatives (Lim, Dey, and Avrahami 2009; Stumpf et al. 2007), in particular rules similar to anchors. Short, disjoint rules are easier to interpret than hierarchies like decision lists or trees (Lakkaraju, Bach, and Leskovec 2016). A number of approaches construct globally interpretable models, many based on rules (Lakkaraju, Bach, and Leskovec 2016; Letham et al. 2015; Wang and Rudin 2015; Wang et al. 2015). With such models, the user should be able to guess the model’s behavior on any example (i.e. perfect coverage). However, these models are not appropriate for many domains, e.g. almost no interpretable rule-based system is suitable for text or image applications, due to the sheer size of the feature space, or are just not accurate enough. Interpretability, in these cases, comes at the cost of flexibility, accuracy, or efficiency (Ribeiro, Singh, and Guestrin 2016a). An alternative is learning a simple (interpretable) model to imitate the black



(a) Original image



(b) Anchor for "beagle"



(c) Images where Inception predicts $P(\text{beagle}) > 90\%$

| | |
|---|------------|
| What animal is featured in this picture ? | dog |
| What floor is featured in this picture? | dog |
| What toenail is paired in this flowchart ? | dog |
| What animal is shown on this depiction ? | dog |

(d) **VQA**: Anchor (bold) and samples from $\mathcal{D}(z|A)$

| | |
|-------------------------------------|----------------|
| Where is the dog ? | on the floor |
| What color is the wall? | white |
| When was this picture taken? | during the day |
| Why is he lifting his paw? | to play |

(e) **VQA**: More example anchors (in bold)

Figure 3: Anchor Explanations for Image Classification and Visual Question Answering (VQA)

box model globally (e.g. a decision tree (Craven and Shavlik 1996) or a set of rules (Sanchez et al. 2015)), but this may yield low human precision. **Simple models are not able to fully capture the behavior of the complex ones, and thus lead users to wrong conclusions, especially since it is not clear when the simple model is faithful.**

To avoid this, *local* model-agnostic explanations explain individual predictions (instead of the whole model at once). These methods provide a trade-off: each explanation is easy to understand even for complex models and tasks, but only captures the behavior of the model on a local region of the input space. The anchor approach falls within this category (and thus can explain complex models like translation and VQA), together with many forms of linear explanations (Baehrens et al. 2010; Ribeiro, Singh, and Guestrin 2016b; Strumbelj and Kononenko 2010). As illustrated pictorially by Figure 2b and concretely in Figure 1b, even the local behavior of a model may be extremely non-linear, leading to poor linear approximations and users being potentially misled as to how the model will behave (e.g. thinking that “not” will usually be positive after seeing Figure 1b (left)). **Linear explanations are also harder to parse and apply than simple rules, as they involve mental calculations.** Finally, even if the black-box model is approximately linear locally, humans may not be able to compute distance functions “correctly”, and may think that a local explanation applies when it does not – the “unclear coverage” problem.

Anchors, on the other hand, make their coverage very clear — the user knows exactly when the explanation for an instance “generalizes” to other instances. By construction, anchors are not only faithful to the original model, but communicate its behavior to the user in such a way that virtually guarantees correct understanding, and thus high precision. Anchors are also able to capture non-linear behavior, even locally. In sum, the anchor approach combines the benefits of local

model-agnostic explanations with the interpretability of rules, constructed in a way to best support human understanding.

Efficiently Computing Anchors

We revisit the problem definition from Eq. (1): given a black-box classifier f , instance x , distribution \mathcal{D} , and the desired level of precision τ , an anchor A is a set of feature predicates on x that achieves $\text{prec}(A) \geq \tau$, where

$$\text{prec}(A) = \mathbb{E}_{\mathcal{D}(z|A)} [\mathbb{1}_{f(x)=f(z)}] . \quad (2)$$

For an arbitrary \mathcal{D} and black-box model f , it is intractable to compute this precision directly. Instead, we introduce a probabilistic definition: anchors satisfy the precision constraint with high probability.

$$P(\text{prec}(A) \geq \tau) \geq 1 - \delta \quad (3)$$

If multiple anchors meet this criterion, those that describe the behavior of a larger part of the input space are preferred, i.e. **ones with the largest coverage**. Formally, we define the coverage of an anchor as the probability that it applies to samples from \mathcal{D} , i.e. $\text{cov}(A) = \mathbb{E}_{\mathcal{D}(z)} [A(z)]$.

We thus define this search for an anchor as the following combinatorial optimization problem:

$$\max_{A \text{ s.t. } P(\text{prec}(A) \geq \tau) \geq 1 - \delta} \text{cov}(A). \quad (4)$$

The number of all possible anchors is exponential, and it is **intractable to solve this problem exactly**. While the search for anchors is similar in spirit to Probabilistic Inductive Logic Programming (ILP) (De Raedt and Kersting 2008) and other rule-finding methods, one crucial difference is that **we do not assume a dataset apriori - instead we have perturbation distributions and a black box model, which we can call to estimate precision and coverage bounds under \mathcal{D} .** While we

Với một \mathcal{D} tùy ý và mô hình hộp đen thì sẽ rất khó đưa ra độ chính xác một cách trực tiếp -> sử dụng một định nghĩa xác suất là anchors thỏa mãn độ chính xác mặc định với xác suất cao. Khi mà nhiều anchor đạt được chỉ tiêu đó thì các anchor đó được xem là nơi có độ bao phủ lớn nhất. Tuy nhiên số lượng anchor có thể tìm thấy là cấp số mũ, nên việc có thể giải quyết vấn đề trên thì rất khó. Việc tìm kiếm anchor giống với thuật toán ILP nhưng điểm khác biệt là không sử dụng dữ liệu apriori, thay vào đó là các phương pháp nhiễu loạn và mô hình hộp đen để điều tra độ chính xác và khoảng bao phủ.

Xây dựng anchor A với quy tắc rõ ràng.
 PP: mỗi vòng lặp sinh ra một tập quy tắc ứng viên sau đó mở rộng A bằng cách thêm vào ví từ đặc trưng (ai). Sau đó xác định quy tắc ứng viên có độ chính xác cao nhất và thay nó với A và cứ lặp lại như thế, cho đến khi quy tắc ứng viên hiện tại thỏa mãn điều kiện ở Eq(3), ta sẽ xác định được desire anchor. Phương pháp này không trực tiếp đi kèm độ bao phủ nhưng thay vì vậy tìm ra anchor ngắn nhất (theo quan điểm là anchor có độ bao phủ tốt nhất và ít khó khăn cho người dùng có thể hiểu được)
 - Để có thể chọn được quy tắc ứng viên với độ chính xác cao nhất, chúng ta phải ước tính độ chính xác trên các quy tắc ứng viên một cách hiệu quả. Vì ta không thể tính độ chính xác một cách chính xác ta chỉ có thể dựa vào các mẫu từ $D(\cdot|A)$ để ước tính độ chính xác của A nhưng số lượng mẫu có thể quá nhiều hoặc quá ít cho ước tính độ chính xác \rightarrow để khắc phục điều này, quan tâm đến tập con tối thiểu được gọi tới f (ít mẫu nhất từ D) để ước tính xem quy tắc ứng cử viên nào có độ chính xác cao nhất.

could in theory generate a very large dataset and then use methods like ILP to find anchors, the number of perturbed samples and predictions from the black box model would be prohibitive, especially in high-dimensional sparse domains such as text. **In order to efficiently explore the model's behavior in the perturbation space, we turn to a multi-armed bandit formulation.**

Bottom-up Construction of Anchors

We first introduce a bottom-up construction of anchors, which we later extend to search over a space of potential anchors. Here, we incrementally construct the anchor A , which is initialized with an *empty* rule, i.e. one that applies to every instance. In each iteration, we generate a number of candidate rules that extend A by one additional feature predicate, $\{a_i\}$, in its definition, i.e. the set of candidate rules in each iteration is $\mathcal{A} = \{A \wedge a_i, A \wedge a_{i+1}, A \wedge a_{i+2}, \dots\}$. We identify the candidate rule with the highest *estimated precision* (as described next), replace A with the selected candidate, and repeat. If the current candidate rule meets the anchor definition in Eq. (3), we have identified our desired anchor and terminate. Although this approach does not directly compute the coverage, and instead tries to **find the shortest anchor, we note that short anchors are likely to have a higher coverage, and require less effort from the users to understand.**

In order to select the best candidate rule in each iteration, we want to estimate the precision of these candidates efficiently. Since we cannot compute the *true* precision, we rely on samples from $\mathcal{D}(\cdot|A)$ to estimate the precision of A ; however, a fixed number of samples may be too many or too few for an accurate estimation. Instead, we are interested in a *minimal* set of calls to f (fewest samples from \mathcal{D}) in order to estimate which candidate rule has the highest *true* precision.

This problem can be formulated as an instance of *pure-exploration multi-armed bandit* problem (Kaufmann and Kalyanakrishnan 2013), i.e. each candidate A is an arm, the true precision of A on $\mathcal{D}(\cdot|A)$ is the *latent* reward, and each pull of the arm A is an evaluation of $\mathbb{1}_{f(x)=f(z)}$ on a sample from $\mathcal{D}(z|A)$. For such a setting, the KL-LUCB (Kaufmann and Kalyanakrishnan 2013) algorithm can be used to identify the rule with the highest precision. The algorithm works by constructing confidence regions based on KL divergence (Cover and Thomas 1991). In each step, the algorithm selects two distinct rules: the best mean (A) and the highest upper bound (A'), and updates their bounds by getting a sample each from $\mathcal{D}(z|A)$ and $\mathcal{D}(z'|A')$, and computing $\mathbb{1}_{f(x)=f(z)}$ and $\mathbb{1}_{f(x)=f(z')}$. **This sampling process continues until the lower bound on A is higher than A' 's upper bound with tolerance $\epsilon \in [0, 1]$.** If A^* is the arm with highest true precision, the following (proved by Kaufmann and Kalyanakrishnan) holds for the true precision of the chosen rule A :

$$P(\text{prec}(A) \geq \text{prec}(A^*) - \epsilon) \geq 1 - \delta \quad (5)$$

Alg 1 presents an outline of this approach. When evaluating if the rule chosen by KL-LUCB is an anchor, we need to be confident it meets our precision criteria. Thus, if for an identified rule A , $\text{prec}_{lb}(A) < \tau$ but $\text{prec}_{ub}(A) > \tau$, we sample from $\mathcal{D}(\cdot|A)$ until either we are confident A is an anchor ($\text{prec}_{lb}(A) > \tau$) or not ($\text{prec}_{ub}(A) < \tau$).

- Một thuật toán giúp cho thực hiện phương pháp này là pure exploration multi-armed bandit problem với cánh tay là một quy tắc ứng viên A và độ chính xác A trên $\mathcal{D}(\cdot|A)$ là phần thưởng tiềm ẩn và khi kéo cánh tay A là một đánh giá ($\mathbb{1}(f(z)=f(x))$) trên một mẫu từ $\mathcal{D}(z|A)$. Thuật toán KL-LUCB được sử dụng để tìm quy tắc ứng viên A có độ chính xác cao nhất, bằng cách xây dựng vùng tin cậy. Trong mỗi bước, thuật toán sẽ chọn hai quy tắc khác biệt nhau: trung bình tốt nhất (A) và giới hạn trên cao nhất (A'), và cập nhật giới hạn của chúng dựa vào mẫu từ $\mathcal{D}(z|A)$ và $\mathcal{D}(z'|A')$ và tính toán. Quá trình lấy mẫu này tiếp tục cho đến khi giới hạn dưới của A cao hơn giới hạn trên của A' với độ chịu đựng là từ 0 đến 1. Nếu A* là cánh tay có độ chính xác tốt nhất thì độ chính xác của A phải lớn hơn hoặc bằng độ chính xác đó A* - độ chịu đựng và thỏa mãn định nghĩa xác suất ở Eq(3).
 - một quy tắc ứng viên A: độ chính xác của giới hạn dưới A nhỏ hơn r nhưng độ chính xác của giới hạn trên của A lớn hơn r
 - A là anchor: độ chính xác của giới hạn dưới A lớn hơn r hoặc độ chính xác của giới hạn trên của A không nhỏ hơn r

Greedy search: tìm kiếm tham lam, tìm kiếm anchor ngắn nhất, với mỗi bước chọn được tối ưu gần với độ xác suất cao. nhưng chỉ duy trì được một quy tắc nhất định, và không trực tiếp quan tâm đến độ bao phủ của anchor mà chỉ tìm anchor ngắn nhất.

Algorithm 1 Identifying the Best Candidate for Greedy

```

function GenerateCands( $\mathcal{A}, c$ )
   $\mathcal{A}_r = \emptyset$ 
  for all  $A \in \mathcal{A}; a_i \in x, a_i \notin A$  do
    if  $\text{cov}(A \wedge a_i) > c$  then           {Only high-coverage}
       $\mathcal{A}_r \leftarrow \mathcal{A}_r \cup (A \wedge a_i)$     {Add as potential anchor}
  return  $\mathcal{A}_r$                              {Candidate anchors for next round}

function BestCand( $\mathcal{A}, \mathcal{D}, \epsilon, \delta$ )
  initialize  $\text{prec}, \text{prec}_{ub}, \text{prec}_{lb}$  estimates  $\forall A \in \mathcal{A}$ 
   $A \leftarrow \arg \max_A \text{prec}(A)$ 
   $A' \leftarrow \arg \max_{A' \neq A} \text{prec}_{ub}(A', \delta)$            { $\delta$  implicit below}
  while  $\text{prec}_{ub}(A') - \text{prec}_{lb}(A) > \epsilon$  do
    sample  $z \sim \mathcal{D}(z|A), z' \sim \mathcal{D}(z'|A')$            {Sample more}
    update  $\text{prec}, \text{prec}_{ub}, \text{prec}_{lb}$  for  $A$  and  $A'$ 
     $A \leftarrow \arg \max_A \text{prec}(A)$ 
     $A' \leftarrow \arg \max_{A' \neq A} \text{prec}_{ub}(A')$ 
  return  $A$ 

```

Algorithm 2 Outline of the Beam Search

```

function BeamSearch( $f, x, \mathcal{D}, \tau$ )
  hyperparameters  $B, \epsilon, \delta$ 
   $A^* \leftarrow \text{null}, \mathcal{A}_0 \leftarrow \emptyset$            {Set of candidate rules}
  loop
     $\mathcal{A}_t \leftarrow \text{GenerateCands}(\mathcal{A}_{t-1}, \text{cov}(A^*))$ 
     $\mathcal{A}_t \leftarrow \text{B-BestCand}(\mathcal{A}_t, \mathcal{D}, B, \delta, \epsilon)$            {LUCB}
    if  $\mathcal{A}_t = \emptyset$  then break loop
    for all  $A \in \mathcal{A}_t$  s.t.  $\text{prec}_{lb}(A, \delta) > \tau$  do
      if  $\text{cov}(A) > \text{cov}(A^*)$  then  $A^* \leftarrow A$ 
  return  $A^*$ 

```

Beam-Search for Anchor Construction

Although the greedy approach we have described so far can find short anchors with the guarantee that, for each step, the choice was near optimal with high probability, it has two major shortcomings. First, due to the greedy nature of the approach, it is only able to maintain a single rule at a time (that it incrementally augments), and thus any suboptimal choice is irreversible. Second, the greedy algorithm is not directly concerned with the coverage of the anchors, and instead returns the shortest anchor that it finds. In order to address both these concerns, we extend the greedy approach to perform a beam-search by maintaining a set of candidate rules, while guiding the search to identify amongst many possible anchors the one that has the highest coverage.

The algorithm is outlined in Algorithm 2. It is similar in structure to the greedy approach, with a set of B current candidates instead of a single one. After generating all the possible candidates rules, we select the B -best candidates to keep based on the KL-LUCB approach with multiple arms (the *Explore- m* setting). For the tolerance $\epsilon \in [0, 1]$, this version of KL-LUCB algorithm returns a set \mathcal{A} of size B that is an ϵ -approximation of \mathcal{A}^* , with high probability.

$$P(\min_{A \in \mathcal{A}} \text{prec}(A) \geq \min_{A' \in \mathcal{A}^*} \text{prec}(A') - \epsilon) \geq 1 - \delta \quad (6)$$

We omit the description of KL-LUCB for this setting, but the intuition is similar to the one in the greedy approach. Further, amongst multiple anchors that we encounter, we output

Beam search: tìm kiếm theo tia pp khắc phục cho 2 điểm yếu của greed search bằng cách mở rộng greed search, duy trì tập quy tắc ứng viên, đồng thời tìm ra hầu hết các anchor có thể và một trong đó với độ bao phủ cao. Có cấu trúc giống greedy, nhưng duy trì tập quy tắc ứng viên B.

Step: sinh ra tập quy tắc ứng viên có thể (B)-> chọn các ứng viên tốt nhất (B-best) bằng cách áp dụng KL-LUCB (trả về tập A có kích thước B là sự xấp xỉ độ chịu đựng của A', nghĩa là chọn độ chính xác nhỏ nhất của quy tắc ứng viên (A) trong A phải lớn hơn bằng độ chính xác nhỏ nhất của quy tắc ứng viên (A') trong A' trừ đi độ chịu đựng.

Với nhiều anchor, chọn anchor có độ bao phủ cao nhất thỏa Eq(4), cũng với điều kiện đó dùng để cắt tia hiệu quả không gian tìm kiếm, nghĩa là không lưu trữ bất kỳ quy tắc cổ độ bao phủ thấp hơn anchor tốt nhất tìm thấy cho đến nay. Bởi vì độ bao phủ của anchor chỉ giảm khi thêm vào mệnh đề

the one with the highest coverage, thus directly optimizing Eq. (4). This condition is also used for efficient pruning of the search space – we do not store any rule that has a lower coverage than that of the best anchor found so far, since the coverage of a rule can only reduce as more predicates are added. The beam-search algorithm is therefore more likely to return an anchor with a higher coverage than the one found by the greedy approach, and thus we use this algorithm for all examples and experiments.

Hyperparameters and Potential Issues

A rule that exactly matches x is always a valid anchor, albeit with very low coverage, and thus, is of little use. Our algorithm can always recover this anchor, and thus is guaranteed to terminate in a bounded number of iterations. In pathological cases, it is possible for KL-LUCB to require a very large number of samples from \mathcal{D} in order to separate two candidate rules with a high confidence; however, this can be alleviated by increasing the tolerance ϵ , the width δ , or by setting a maximum number of samples. In practice, all explanations present in this paper were generated in a few seconds to a few minutes. We set these parameters to reasonable values, $B = 10$, $\epsilon = 0.1$, $\delta = 0.05$, and leave an analysis of the sensitivity of our approach to these for future work.

So far, we focused on computing anchors for individual predictions. In order to gain a more complete understanding of how the model works, the user needs to examine multiple explanations. Instead of randomly selecting which anchors to show to the user, we would like to identify an optimal set of anchors that represent this global behavior, thereby reducing the user effort. By observing that such an objective is submodular, we propose an approach for submodular-pick (SP) in Ribeiro, Singh, and Guestrin (2016b) that we adapt to this setting. In particular, the approach selects K anchors that cover as many instances in the validation set as possible. We use an iterative, greedy method that provides guarantees on the quality of our solution, due to the submodular nature of the optimization (Krause and Golovin 2014).

có thể LUCB yêu cầu một lượng lớn mẫu để tách thành 2 quy tắc ứng viên với độ tin cậy cao -> điều chỉnh tham số sao cho hợp lý và phù hợp cho các công việc tương lai.

Experiments

We evaluate anchor explanations for complex models on a number of tasks, primarily focusing on how they facilitate accurate predictions by users (simulated and human) on the behavior of the models on unseen instances. Code and the data for all the experiments is available at <https://github.com/marcotcr/anchor-experiments>.

Simulated Users

For simulated users, we use the tabular datasets previously mentioned (*adult*, *rcdv* and *lending*). Each dataset is split such that models are trained with the *training* set, explanations are produced for instances in the *validation* set, and evaluated on instances in the *test* set. For each dataset, we train three different models: logistic regression (**lr**), 400 gradient boosted trees (**gb**) and a multilayer perceptron with two layers of 50 units each (**nn**). We generate both linear LIME (Ribeiro, Singh, and Guestrin 2016b) and anchor explanations for them.

Một tập dữ liệu gồm training, validation, test: chạy mô hình trên tập train, tạo đánh giá trên tập validation, đánh giá trên tập test. Tiến hành tính độ bao phủ và độ chính xác của từng tập dữ liệu theo hai hướng là anchor và lime. Nhưng vấn đề đặt ra ở đây là người dùng thực sẽ áp dụng đánh giá Lime như thế nào. Lý tưởng, là áp dụng Lime cho các ví dụ gần gũi, nhưng chúng ta không chắc chắn rằng khoảng cách hàm và ngưỡng threshold cho "gần gũi" là cái gì hoặc nếu người dùng tạo hàm khoảng cách dựa trên nhu cầu của bản thân. Một cách rõ ràng, ta thấy được phương pháp anchor có độ chính xác cao cho toàn bộ dữ liệu và mô hình hơn so với khi dùng lime-n (lời giải thích không quan tâm đến khoảng cách). Bởi vì độ chính xác là điều kiện tiên quyết trong khả năng giải thích của mô hình. Nên chúng ta áp dụng giải thích tuyến tính cho ra một xác suất vượt qua ngưỡng nhất định (đặt ngưỡng trên khoảng cách sẽ tạo ra kết quả tồi hơn) - lime-t. Như ta thấy được rằng độ phủ sau khi áp dụng hai phương pháp Anchor và Lime-t lại không phân thắng thua với nhau -> Anchor mang lại hiệu suất tốt hơn Lime.

| | | Precision | | Coverage | |
|---------|----------|-----------|--------|----------|--------|
| | | anchor | lime-n | anchor | lime-t |
| adult | logistic | 95.6 | 81.0 | 10.7 | 21.6 |
| | gbt | 96.2 | 81.0 | 9.7 | 20.2 |
| | nn | 95.6 | 79.6 | 7.6 | 17.3 |
| rcdv | logistic | 95.8 | 76.6 | 6.8 | 17.3 |
| | gbt | 94.8 | 71.7 | 4.8 | 2.6 |
| | nn | 93.4 | 65.7 | 1.1 | 1.5 |
| lending | logistic | 99.7 | 80.2 | 28.6 | 12.2 |
| | gbt | 99.3 | 79.9 | 28.4 | 9.1 |
| | nn | 96.7 | 77.0 | 16.6 | 5.4 |

Table 4: Average precision and coverage with **simulated users** on 3 tabular datasets and 3 classifiers. *lime-n* indicates direct application of LIME to unseen instances, while *lime-t* indicates a threshold was tuned using an oracle to achieve the same precision as the anchor approach. The anchor approach is able to maintain very high precision, while a naive use of linear explanations leads to varying degrees of precision.

thay vì chúng ta lựa chọn các anchor một cách ngẫu nhiên, thì chúng ta dùng SP để chọn một tập anchor tối ưu đa dạng và đại diện -> biểu diễn được hành vi toàn cục cho người dùng. Nghĩa là tập ứng viên đó phải có độ bao phủ nhiều trường hợp trong tập validation nhất có thể.

When simulating users, we compute coverage (what fraction of the instances they predict after seeing explanations) and precision (what fraction of the predictions were correct) on the complete test set. For each dataset, model, and explanation type, we compute these metrics for the explanation of each instance in the validation data. Simulating when an anchor *applies* is clear. It is not obvious, however, how real users would use LIME explanations. Ideally, they should only apply explanations to examples that are close, but it is not clear what the distance function and the threshold for "close" should be, or if users compute distances on demand. Therefore, in this section, we simulate different behaviors, and perform a study with real users in the following section.

In Table 4 (left), we show the average precision for anchor and LIME, assuming users always apply the LIME explanation without any regard to distance (we call such a user *lime-n*, for naive). It is clear that the anchor approach is able to deliver on the promise of high average precision, for all datasets and models. If users apply LIME naively, on the other hand, they get widely differing levels of precision. Since high precision is a prerequisite for interpretability, we simulate a user that only makes a prediction with LIME if the application of the linear explanation yields a probability above a certain threshold (setting a threshold on the distance produced strictly worse results), and call this user *lime-t*. We tune the threshold values for each dataset/model pair in order to obtain the same average precision as the anchor approach on the test set, so that coverage is comparable. A real user would not be able to perform this tuning, as (1) we are "cheating" by looking at the test set, and (2) the threshold values found range from 67% to 91%, and often with huge variation in the same dataset for different models. We show the average test coverage of the validation set explanations for anchor and lime-t in Table 4 (right). There is no clear winner in terms of coverage, thus demonstrating that even with the impossibly tuned thresholds, LIME is not able to outperform anchors.

Although the user is often interested in specific expla-

| Method | Precision | | | | Coverage (perceived) | | | | Time/pred (seconds) | | | |
|-----------|-----------|------|------|------|----------------------|------|------|------|---------------------|-----------|-----------|-----------|
| | adult | rcdv | vqa1 | vqa2 | adult | rcdv | vqa1 | vqa2 | adult | rcdv | vqa1 | vqa2 |
| No expls | 54.8 | 83.1 | 61.5 | 68.4 | 79.6 | 63.5 | 39.8 | 30.8 | 29.8 ± 14 | 35.7 ± 26 | 18.7 ± 20 | 13.9 ± 20 |
| LIME(1) | 68.3 | 98.1 | 57.5 | 76.3 | 89.2 | 55.4 | 71.5 | 54.2 | 28.5 ± 10 | 24.6 ± 6 | 8.6 ± 3 | 11.1 ± 8 |
| Anchor(1) | 100.0 | 97.8 | 93.0 | 98.9 | 43.1 | 24.6 | 31.9 | 27.3 | 13.0 ± 4 | 14.4 ± 5 | 5.4 ± 2 | 3.7 ± 1 |
| LIME(2) | 89.9 | 72.9 | - | - | 78.5 | 63.1 | - | - | 37.8 ± 20 | 24.4 ± 7 | - | - |
| Anchor(2) | 87.4 | 95.8 | - | - | 62.3 | 45.4 | - | - | 10.5 ± 3 | 19.2 ± 10 | - | - |

Table 5: **Results of the User Study.** Underline: significant w.r.t. anchors in the same dataset and same number of explanations. Results show that users consistently achieve high precision with anchors, as opposed to baselines, with less effort (time).

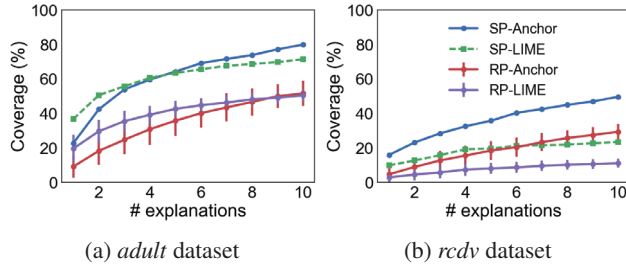


Figure 4: Coverage on the test set as the simulated user sees more explanations, at the same precision level. While there is no clear winner for random explanations, anchors are better when explanations are picked using submodular-pick.

Việc áp dụng SP-Pick vào anchors sẽ mang lại những tập ứng viên đa dạng, mang tính đại diện và không trùng lặp -> điều đó dẫn đến độ bao phủ của các phương pháp sử dụng SP sẽ luôn cao. Anchor có độ bao phủ cao hơn so với LIME nếu có cùng độ chính xác nhưng trong thực tế, không biết được người dùng có thể đạt được độ chính xác cao hơn với LIME hay không?

nations, most users would prefer a set of explanations that explain most of the model with as little effort on their part as possible - explanations picked using the submodular procedure described before. In Figure 4, we show the coverage (for the same precision level) for *gb* in two of the datasets (we omit the other models/dataset due to space, but the results are similar) as the user sees more explanations, chosen either via submodular pick (SP-LIME and SP-Anchor) or at random (RP-LIME and RP-Anchor). The results indicate that while the average coverage of random explanations is low (e.g. 4.8% for *rcdv*), selecting the right set of explanations with submodular pick can give users an understanding of the model’s *global* behavior (e.g. ~50% after only 10 explanations). The anchor approach also yields better coverage for the same precision - even though it is unclear if real users can achieve such high precision with LIME.

User study

We ran a user study with 26 users – students who had or were taking a machine learning course – so we could rely on familiarity with concepts such as “model”, “prediction”, and “cross validation”. For this study, we used the *adult* and *rcdv* datasets, followed by a multiple-choice VQA system (Ren, Kiros, and Zemel 2015) on two images. While the VQA model predicts one of 1000 labels, we restrict it to the 5 most common answers predicted on questions in \mathcal{D} , in order to reduce visual overload.

For each dataset and explanation type, we want to evaluate if users are able to predict the behavior of the model on

Thông qua ví dụ này càng chứng minh thêm được rằng khi có được lời giải thích từ anchors, độ chính xác và độ bao phủ được cải thiện rất nhiều. Và thông qua các anchors, người dùng có thể nhìn nhận được các trường hợp tương tự và xác định được “I don’t know” đối với trường hợp không biết -> độ bao phủ tốt.

Hầu hết mọi người sẽ thích dùng anchor nhưng vẫn có người thấy được rằng trong thực tế độ chính xác của LIME có thể cao hơn (vấn đề được đề cập xuyên suốt bài).

Rất dễ để áp dụng anchor so với việc kết hợp các trọng số của LIME, đặc biệt đối với nhiều lời giải thích.

unseen instances. Our set up for the *adult* and *rcdv* datasets consists of the users first browsing through 10 predictions without any explanations, then with one, and two LIME or anchor explanations. They are asked to predict the behavior of the classifier on 10 random test instances before and 10 instances after seeing each round of explanations. **The user then goes through the same procedure on the other dataset, with the explanation type that was not the one used for the first one.** We ask subjects to only make predictions if they are very confident, and to select “I don’t know” otherwise. We measure coverage as the fraction of instances where users made a prediction other than “I don’t know” (i.e. their perceived coverage), and only measure precision in these instances. This process is repeated for the two VQA images - half the users see LIME for the first and then anchor for the second, and vice versa for the other half, and predict the model’s answers on 20 questions before and after explanations. The explanations are comparable in size: LIME explanations had at most 5 terms in all datasets, while anchors varied from 1 to 5, depending on each individual prediction.

The results in Table 5, where LIME(1) refers to results after one LIME explanation and so on, show that users with anchors achieve high-precision - around 95% for all of the combinations, except for Anchor(2) in *adult*. The coverage of users with anchors grows with a second explanation on both datasets. Precision with LIME, on the other hand, varies dramatically, and for VQA1, is worse than no explanations. The subjects made mostly correct predictions when using anchors (high precision), and knew to select “I don’t know” when an instance was not covered by the explanation. In contrast, with LIME or no explanations, users thought they could make confident predictions more often, even though their precision was considerably lower. Further, it took dramatically less time to understand and use anchors as compared to linear explanations, across all datasets and tasks. On a poll, 21/26 of users preferred anchors, and 24/26 said they would be more precise with anchors; interestingly, the **2 users who said they would be more precise with LIME were actually more precise with anchors.** Many commented that it was **easier to apply anchors than combining the weights of LIME explanations, especially with multiple explanations.** They also felt more confident in their predictions with anchors.

The user study confirms our hypotheses: it is much easier for users to understand the coverage of anchor explanations as opposed to linear explanations, and to achieve high-precision

understanding of the model’s behavior (as measured by predicting it on new instances). Anchors are also easier to comprehend, and take less effort in applying, as reflected in their times and qualitative feedback.

Limitations and Future Work

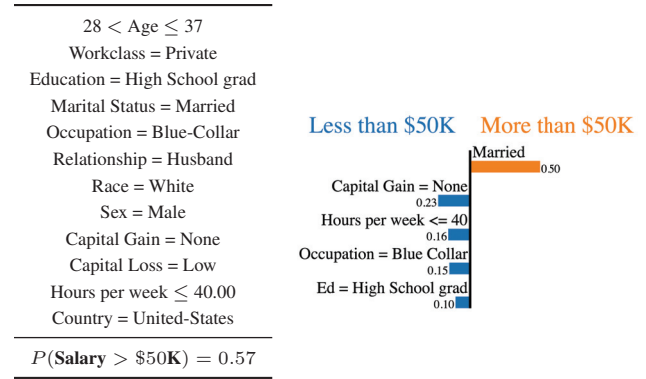
Having demonstrated the flexibility and usefulness of the anchor approach for a wide variety of domains, and having compared it to the state-of-the-art, we now turn to its limitations and opportunities for future work.

Overly specific anchors: Predictions that are near a boundary of the black box model’s decision function, or predictions of very rare classes may require very specific “sufficient conditions”, and thus their anchors may be complex and provide low coverage. We give an example in Figure 5 (*adult* dataset), where a particular prediction is very near the boundary of the decision function – almost any change to the instance results in a change in prediction. While the very specific anchor in Figure 5c communicates to the user that the conditions necessary for the prediction are very specific, it does not generalize well to other instances, due to its narrowness. It also does not give much insight into the model’s behavior besides the fact that the instance is near a decision boundary. In cases like these, a linear LIME explanation (Figure 5b) may be preferred due to the potential insights it gives, with the caveat that users may still generalize incorrectly due to unclear coverage.

Potentially conflicting anchors: When using the anchor approach “in the wild”, two or more anchors with different predictions may apply to the same test instance. While possible, this situation is unlikely for two reasons: (1) the high probability precision guarantee that anchors have by construction, and (2) the submodular objective in the pick procedure encourages a set of anchors with low overlap. If this were to happen in a real situation, we would want to alert the user, suggest further investigation, and maybe suggest increasing the precision threshold.

Complex output spaces: For certain problems where the output is structured and complex, there is a variety of explanations that may be useful. In this work, we restrict ourselves to explaining certain functions of the output, such as in Tables 1 and 2, leaving the task of explaining the full output space to future work. We emphasize that this is a problem that is not specific to the anchor approach, but still an open problem in the explanation literature. Even for a “simpler” output space such as the one present in the multi-label classification setting (Tsoumakas and Katakis 2006), it is not clear if the best option would be to explain each label individually or the set of predicted labels as a single label. The former could overwhelm the user if the number of labels is too large, while the latter may lead to non intuitive, or overly complex explanations.

Realistic perturbation distributions: All perturbation-based explanation methods depend on a local perturbation distribution that is expressive enough to reveal the model’s behavior, while acting on components that are sufficiently interpretable. Finding such distributions for some domains re-



(a) Instance and prediction (b) LIME explanation

IF Country = United-States **AND** Capital Loss = Low
AND Race = White **AND** Relationship = Husband
AND Married **AND** 28 < Age ≤ 37
AND Sex = Male **AND** High School grad
AND Occupation = Blue-Collar
THEN PREDICT Salary > \$50K

(c) An anchor explanation

Figure 5: Explaining a prediction near the decision boundary in the UCI adult dataset.

mains a challenge - for example, the perturbations for images provided explanations that led to some insight, but cannot be used for comparison of explanations across images. Designing such distributions is a line of research that would benefit multiple explanation methods.

Conclusions

We have argued that high precision and clear coverage are crucial for interpretable explanations of a model’s local behavior. We introduced a novel family of rule-based, model-agnostic explanations called *anchors*, designed to exhibit both these properties. Anchors highlight the part of the input that is sufficient for the classifier to make the prediction, making them intuitive and easy to understand. We demonstrated the flexibility of the anchor approach by explaining predictions from a variety of classifiers on multiple domains. In a user study, we showed that anchors not only lead to higher human precision than linear explanations, but also require less effort to understand and apply.

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Các anchor đặc biệt, nghĩa là dự đoán của nó nằm gần ở giới hạn của hàm dự đoán của hộp đen, hoặc là dự đoán của một trường hợp rất hiếm. Nên hầu hết việc thay đổi các trường hợp sẽ dẫn đến thay đổi dự đoán -> anchor rất phức tạp và độ bao phủ thấp. -> trong TH này, LIME sẽ được ưa chuộng vì những thông tin tiềm năng nó đem lại nhưng vẫn có thể sai vì khả năng phủ sóng không rõ ràng.

Mâu thuẫn giữa các anchor: hai hoặc nhiều neo với dự đoán khác nhau có thể áp dụng cho cùng một trường hợp kiểm tra. Mặc dù có thể xảy ra, tình huống này không thường xảy ra vì hai lý do: (1) đảm bảo độ chính xác cao mà neo có từ quy trình xây dựng, và (2) các tiêu submodular pick khuyến nghị một tập hợp các anchor có độ chồng lấn thấp. Nếu tình huống này xảy ra trong thực tế, chúng tôi muốn thông báo cho người dùng, đề xuất điều tra sâu hơn và có thể đề xuất tăng ngưỡng độ chính xác.

Nhiệm vụ giải thích toàn bộ không gian đầu ra: chưa rõ liệu lựa chọn tốt nhất có phải giải thích từng nhân một hay tập hợp các nhân dự đoán như một nhân duy nhất. Lựa chọn trước có thể làm cho người dùng bị quá tải nếu số lượng nhân quá lớn, trong khi lựa chọn sau có thể dẫn đến giải thích không trực quan hoặc quá phức tạp.

Tất cả các phương pháp giải thích dựa trên sự nhiễu loạn phụ thuộc vào một phân phối nhiễu địa phương đủ để tiết lộ hành vi của mô hình, đồng thời tác động lên các thành phần đủ có thể giải thích. Tìm ra những phân phối như vậy cho một số lĩnh vực là thử thách chính.

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