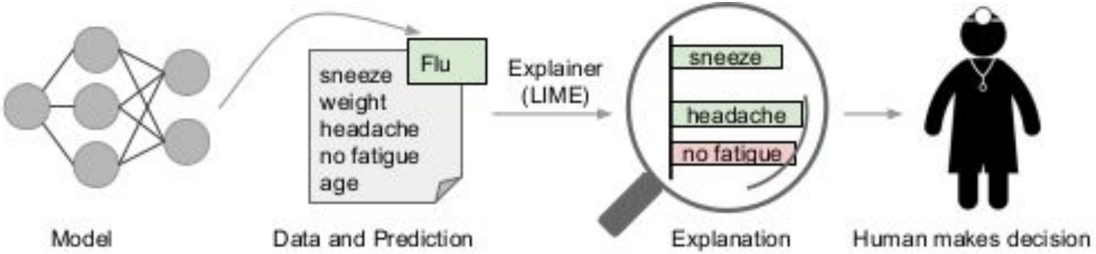
LIME

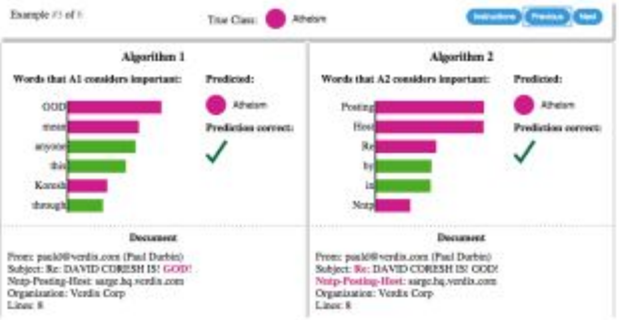
“Why Should I Trust You?”
Explaining the Predictions of Any Classifier
KDD '16

Introduction

- With the increase in ML in tech, human should be able to trust the model.
- Trusting comprises of:
  - Trusting prediction
  - Trusting the model as a whole
- LIME: is an algorithm that can explain predictions of any classifier.
- SP-LIME: LIME with submodule optimization.

Example





- With the help of which, humans with more domain knowledge of the problem will be able to collaborate.
- To ensure that features such as PARENTID do not contribute to the classification.

Desired Characteristics for Explainers

- They must be interpretable
  - Explanations should be easy to understand
- Local fidelity
  - Prediction should be locally faithful
  - Model should behave similarly around the vicinity of the instance.
- Model-agnostic
  - Should be able to explain any model

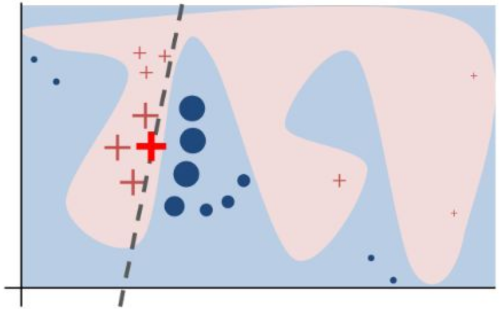


Figure 3: Toy example to present intuition for LIME. The black-box model's complex decision function f (unknown to LIME) is represented by the blue/pink background, which cannot be approximated well by a linear model. The bold red cross is the instance being explained. LIME samples instances, gets predictions using f, and weighs them by the proximity to the instance being explained (represented here by size). The dashed line is the learned explanation that is locally (but not globally) faithful.

Basics - Interpretable Data Representation

- Explainer should use only interpretable representation
- Example
  - for text classification is a binary vector indicating the presence or absence of a word,
- This does not restrict the model, only the explainer.

Loss function

- $\Omega(g)$ Is the measure of complexity of Explainer g
  - Ex, depth of decision tree.
  - Responsible for interpretability
- Model being explained is denoted by $f : \mathbb{R}^d \to \mathbb{R}$.
- $\pi_x(z)$ Is the proximity measure between z and x
  - Responsible for ensuring local fidelity
- $\mathcal{L}(f, g, \pi_x)$ Measures how unfaithful g is in approximating f in locality $\pi_x(z)$

$$\xi(x) = \underset{g \in G}{\operatorname{argmin}} \ \mathcal{L}(f, g, \pi_x) + \Omega(g)$$

Loss function

$$\mathcal{L}(f, g, \pi_x) = \sum_{z, z' \in \mathcal{Z}} \pi_x(z) \left(f(z) - g(z')\right)^2$$

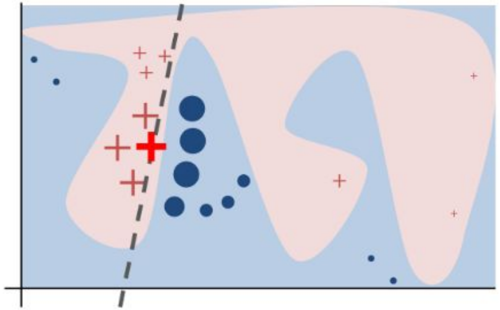
$$\pi_x(z) = exp(-D(x, z)^2/\sigma^2)$$

Algorithm

Algorithm 1 Sparse Linear Explanations using LIME

Require: Classifier f, Number of samples N
Require: Instance x, and its interpretable version x'
Require: Similarity kernel π_x, Length of explanation K

$\mathcal{Z} \leftarrow \{\}$
for $i \in \{1, 2, 3, ..., N\}$ **do**
  $z'_i \leftarrow sample\_around(x')$
  $\mathcal{Z} \leftarrow \mathcal{Z} \cup \langle z'_i, f(z_i), \pi_x(z_i) \rangle$
end for
$w \leftarrow$ K-Lasso$(\mathcal{Z}, K)$ ▷ with z'_i as features, $f(z)$ as target
return w



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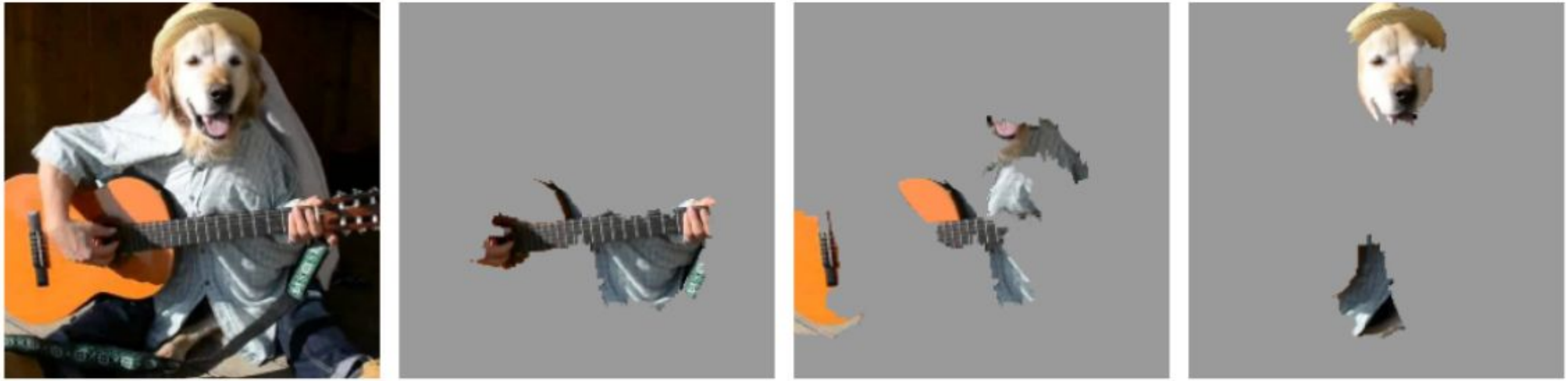
Example - Image



(a) Original Image (b) Explaining *Electric guitar* (c) Explaining *Acoustic guitar* (d) Explaining *Labrador*

Figure 4: Explaining an image classification prediction made by Google's Inception neural network. The top 3 classes predicted are "Electric Guitar" ($p = 0.32$), "Acoustic guitar" ($p = 0.24$) and "Labrador" ($p = 0.21$)

SUBMODULAR PICK FOR EXPLAINING MODELS

Algorithm 2 Submodular pick (SP) algorithm

Require: Instances X, Budget B
  for all $x_i \in X$ **do**
    $\mathcal{W}_i \leftarrow$ **explain**(x_i, x_i') ▷ Using Algorithm 1
  end for
  for $j \in \{1 \ldots d'\}$ **do**
    $I_j \leftarrow \sqrt{\sum_{i=1}^{n} |\mathcal{W}_{ij}|}$ ▷ Compute feature importances
  end for
  $V \leftarrow \{\}$
  while $|V| < B$ **do** ▷ Greedy optimization of Eq (4)
    $V \leftarrow V \cup \text{argmax}_i \, c(V \cup \{i\}, \mathcal{W}, I)$
  end while
  return V

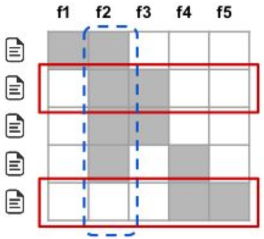
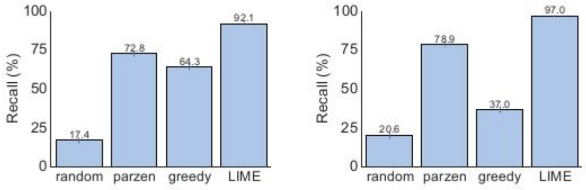


Figure 5: Toy example $\mathcal{W}$. Rows represent instances (documents) and columns represent features (words). Feature f2 (dotted blue) has the highest importance. Rows 2 and 5 (in red) would be selected by the pick procedure, covering all but feature f1.

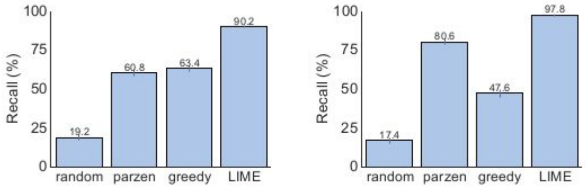
$$c(V, \mathcal{W}, I) = \sum_{j=1}^{d'} \mathbb{1}_{[\exists i \in V : \mathcal{W}_{ij} > 0]} I_j$$

Experiments



(a) Sparse LR (b) Decision Tree

Figure 6: Recall on truly important features for two interpretable classifiers on the books dataset.



(a) Sparse LR (b) Decision Tree

Figure 7: Recall on truly important features for two interpretable classifiers on the DVDs dataset.

Experiment

- They consider a prediction trustworthy if it does not change with removal of untrustworthy feature.
- Untrustworthy features are selected randomly 25% of total features (identified by users)
- For Lime after removing untrustworthy features in explanation, if prediction changes then it is untrustworthy

Table 1: Average F1 of *trustworthiness* for different explainers on a collection of classifiers and datasets.

	Books				DVDs			
	LR	NN	RF	SVM	LR	NN	RF	SVM
Random	14.6	14.8	14.7	14.7	14.2	14.3	14.5	14.4
Parzen	84.0	87.6	94.3	92.3	87.0	81.7	94.2	87.3
Greedy	53.7	47.4	45.0	53.3	52.4	58.1	46.6	55.1
LIME	**96.6**	**94.5**	**96.2**	**96.7**	**96.6**	**91.8**	**96.1**	**95.6**

“Husky vs Wolf”- insight from LIME

(a) Husky classified as wolf (b) Explanation

Figure 11: Raw data and explanation of a bad model’s prediction in the “Husky vs Wolf” task.

	Before	After
Trusted the bad model	10 out of 27	3 out of 27
Snow as a potential feature	12 out of 27	25 out of 27

Table 2: “Husky vs Wolf” experiment results.

Conclusion

- Lime is introduced as an modular and extensible approach to faithfully explaining the predictions
- SP-Lime was also introduced which helped in selecting non redundant features.