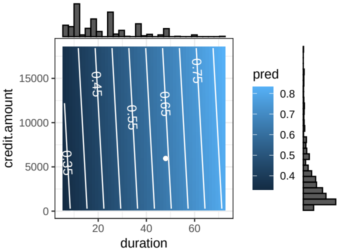
Interpretable Machine Learning

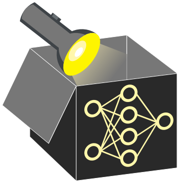
Local Explanations: Lime Examples



Learning goals

- See real-world data examples
- See application to image and text data

EXAMPLE: CREDIT SCORING (TABULAR DATA)



- **Black-box model $\hat{f}_{bad}$:** SVM with RBF kernel (predicts probability of bad credit risk)
- **Instance to explain x:** First row in the dataset, with $\hat{f}_{bad}(\mathbf{x}) = 0.658$

duration	sex	credit.amount	purpose	housing	age	saving	checking	...
48	female	5951	radio/TV	own	22	little	moderate	...

- **Surrogate model:** LASSO, restricted to 5 non-0 feats (via regularization)
- **Training data for surrogate:** Samples **z**, weighted by Gower dist. to **x**

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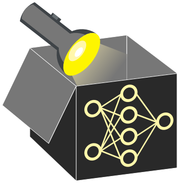

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- **Surrogate model:** LASSO, restricted to 5 non-0 feats (via regularization)
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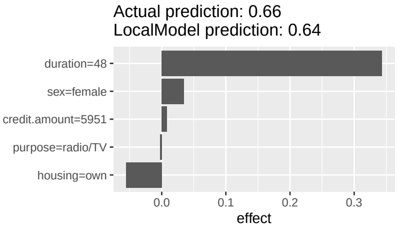
- **Prediction:** $\hat{g}(\mathbf{x}) = 0.640$ vs. $\hat{f}_{bad}(\mathbf{x}) = 0.658$

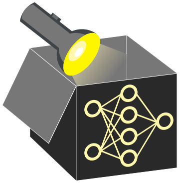
$\rightsquigarrow$ $\hat{g}$ provides good local approx. of $\hat{f}_{bad}$, but omits several features

$\rightsquigarrow$ Small mismatch reflects trade-off: **interpretability vs. fidelity**

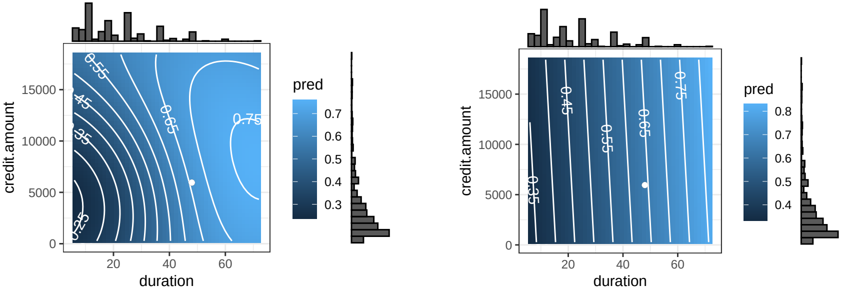


Interpretation: Prediction is mainly driven by loan duration, with small positive effect from sex and credit.amount, and negative contributions from housing and purpose.

EXAMPLE ON CREDIT DATASET (CONT'D)



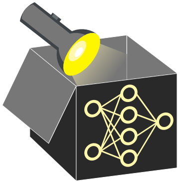
- 2D ICE plots (pred. surface plots) for `duration` and `credit.amount`
- Illustration how $\hat{g}$ linearly approximates nonlinear decision surface of $\hat{f}_{bad}$



- **Left:** 2D ICE plot of $\hat{f}_{bad}$ showing decision surface
- **Right:** Linear approximation by surrogate model $\hat{g}$.
  $\rightsquigarrow$ White dot indicates input $\mathbf{x}$ to be explained
  $\rightsquigarrow$ Histograms show marginal distribution of features in training data

LIME FOR TEXT DATA

▸ "Shen, Ian," 2019



LIME can also be applied to text data:

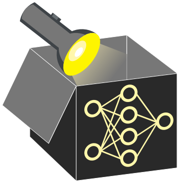
- Raw text representations:
  - Binary vector indicating the presence or absence of a word
  - A vector of word counts
- Examples for *"This text is the first text."* and *"Finally, this is the last one."*:

this	text	is	the	first	finally	last	one
1	2	1	1	1	0	0	0
1	0	1	1	0	1	1	1

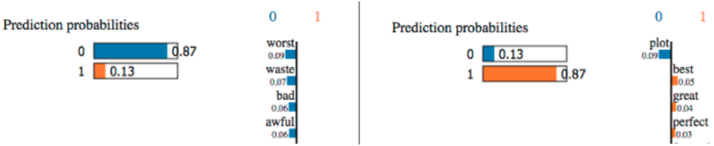
- **Sampling**: Randomly set the entry of individual words to 0; equal to removing all occurrences of this word in the text.
- **Proximity**: Exponential kernel with cosine distance.
  - Neglects words that do not occur in both texts
  - Measures the distance irrespective of the text size

LIME FOR TEXT DATA (CONT'D)

▸ "Shen, Ian," 2019

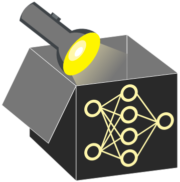


- Random forest classifier labeling movie reviews from IMDB
  - 0: negative
  - 1: positive
- Surrogate model is a sparse linear model



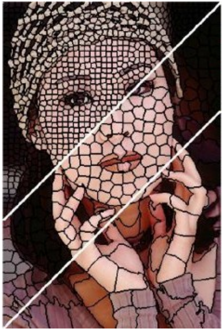
Words like "worst" or "waste" indicate negative review while words like "best" or "great" indicate positive review

LIME FOR IMAGE DATA



LIME also works for image data:

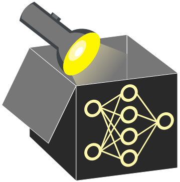
- **Idea**: Each obs. is represented by a binary vector indicating the presence or absence of superpixels ▸ "Achanta et al." 2012
- Superpixels are interconnected pixels with similar colors (absence of a single pixel might not have a (strong) effect on the prediction)
- **Warning**: Size of superpixels needs to be determined before the segmentation takes place
- **Sampling**: Randomly switching some of the super pixels "off", i.e., by coloring some superpixels uniformly



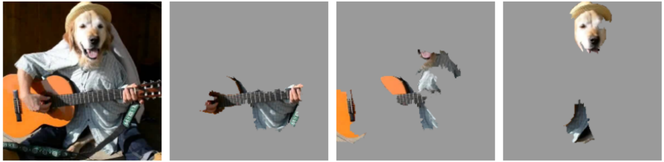
Example for superpixels of different sizes

LIME FOR IMAGE DATA (CONT'D)

▸ "Ribeiro." 2016



- Explaining prediction of pre-trained inception neural network classifier
- **Sampling**: Graying out all superpixels besides 10 superpixels
- **Surrogate**: Locally weighted sparse linear models
- **Proximity**: Exponential kernel with euclidean distance



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

Top 3 classes predicted