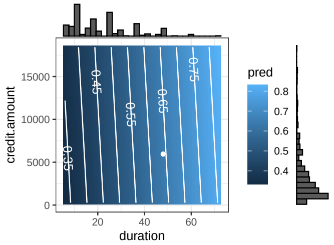
Interpretable Machine Learning

LIME Examples



Learning goals

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

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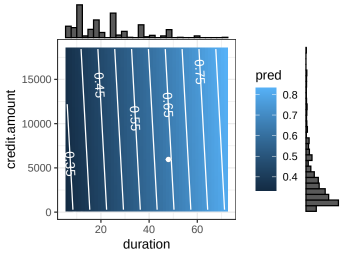
Local Explanations: LIME

LIME Examples



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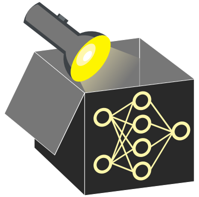
LIME EXAMPLE: CREDIT SCORING (TABULAR DATA)



- **Black-box model $\hat{f}_{bad}$:** SVM with RBF kernel (predicts prob. of bad credit risk)
- **Instance to explain $\mathbf{x}$:** 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-zero features (via regularization)
- **Training data for surrogate:** Samples $\mathbf{z}$, weighted by Gower distance to $\mathbf{x}$

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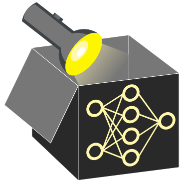

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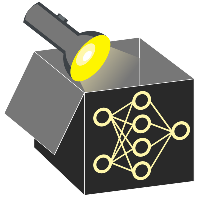

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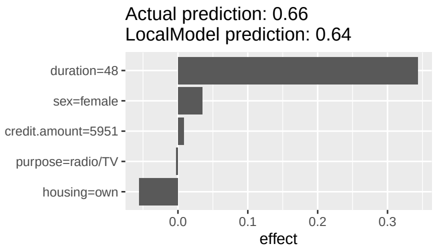
- **Prediction:**
  $\hat{g}(\mathbf{x}) = 0.640$ vs. $\hat{f}_{bad}(\mathbf{x}) = 0.658$

$\rightsquigarrow$ $\hat{g}$ provides good local approximation 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.

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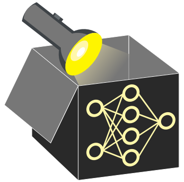

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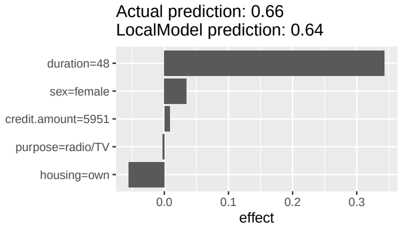

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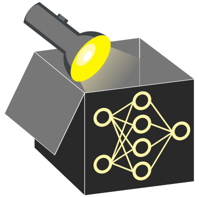
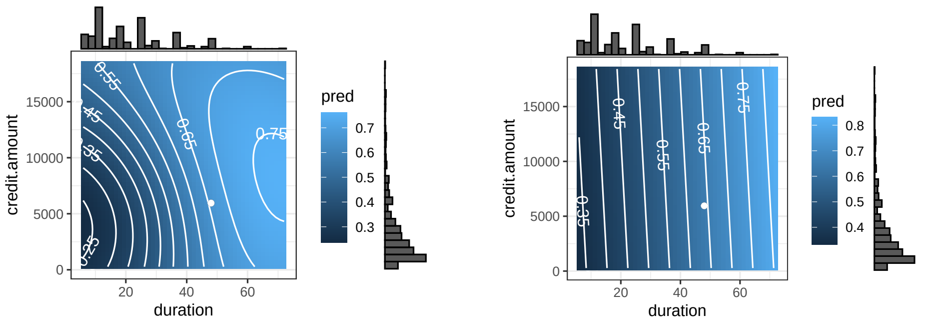
EXAMPLE ON CREDIT DATASET (CONT'D)



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



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

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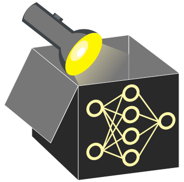

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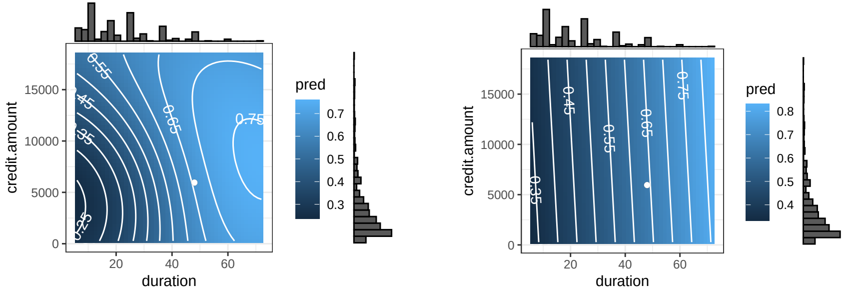

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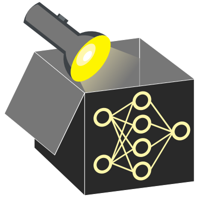
LIME FOR TEXT DATA Shen, Ian, (2019)



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

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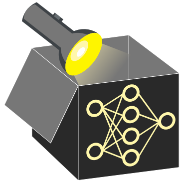

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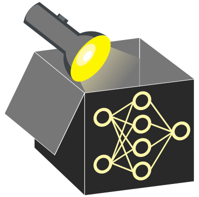
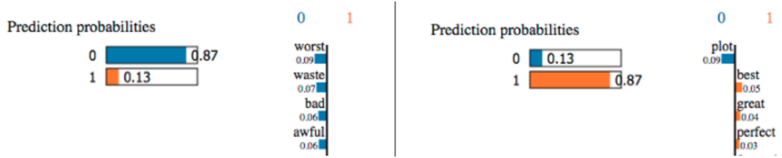


- Random forest classifier labeling movie reviews from IMDB
  - 0: negative
  - 1: positive
- Surrogate model is a sparse linear model



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

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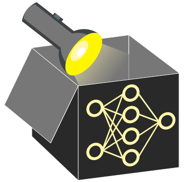

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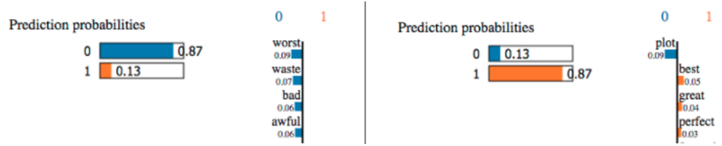

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LIME FOR IMAGE DATA

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

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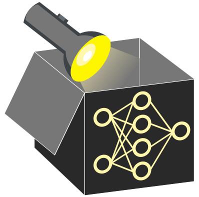
LIME FOR IMAGE DATA (CONT'D) ▸ Ribeiro. 2016



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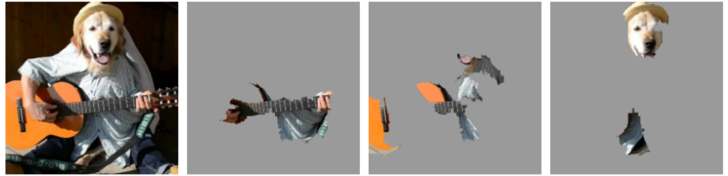
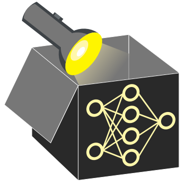


(a) Original Image (b) Explaining *Electric guitar* (c) Explaining *Acoustic guitar* (d) Explaining *Labrador*

Top 3 classes predicted

LIME FOR IMAGE DATA (CONT'D) ▸ RIBEIRO_2016



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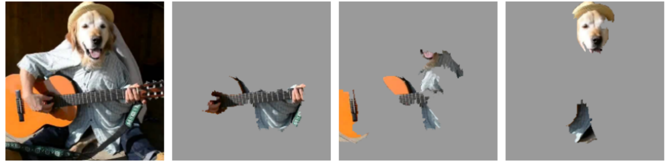

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