Model Agnostic Methods for Interpretability

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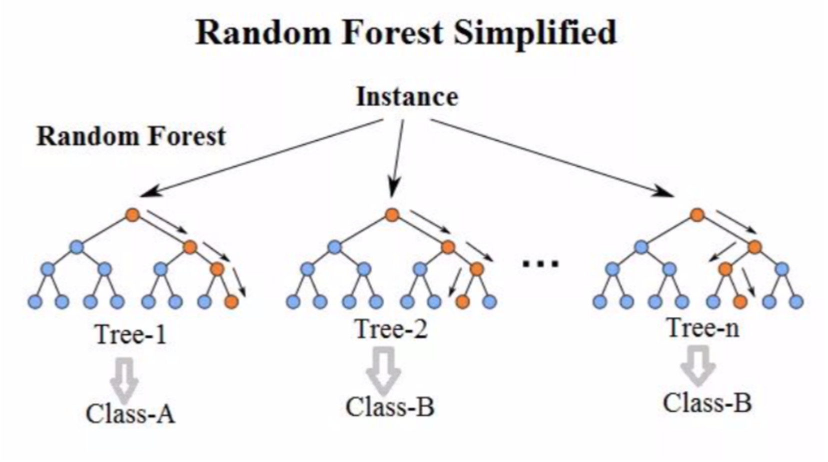
Some Models are hard to interpret

Ensemble models (random forest, boosting, etc…)

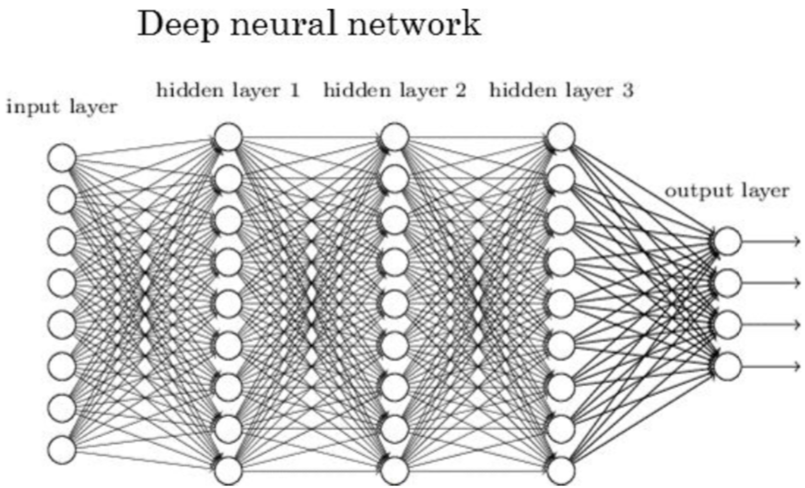
- Hard to understand the role of each feature
- Usually comes with **feature importance**
- Doesn’t tell us if feature affects decision positively or negatively



Some Models are really hard to interpret

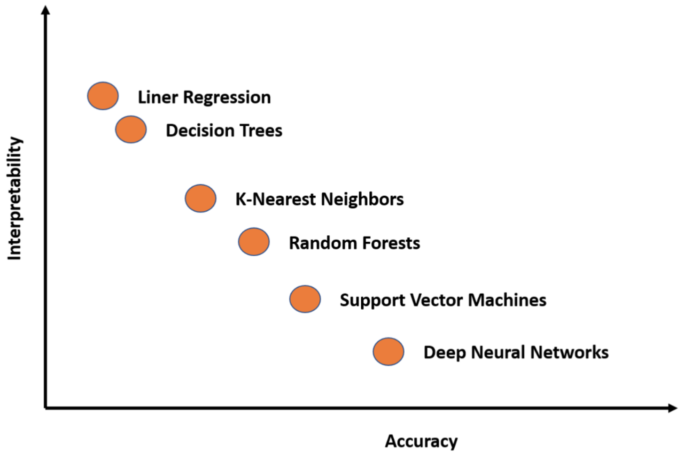
Deep Neural Networks

- No straightforward way to relate input to output layer
- Millions of parameters
- “Black-Box”



Use only simple models?

- Sticking to simpler models is the best way to be confident about interpretation
- However, more complex models such as ensembles and neural network can provide better performance



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Use only simple models?

Model agnostic techniques allows usage of more complex models without losing all interpretability power

Black Box → Model Agnostic Methods

White Box → Model Specific Methods

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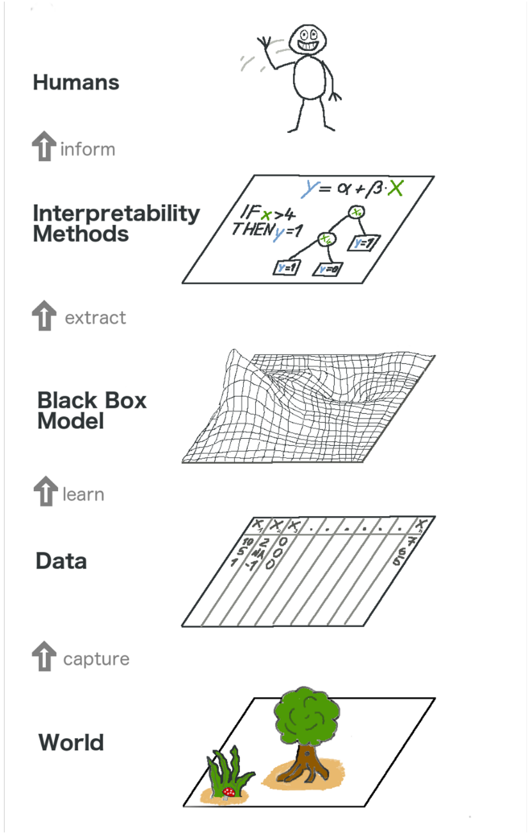
Model Agnostic Interpretability



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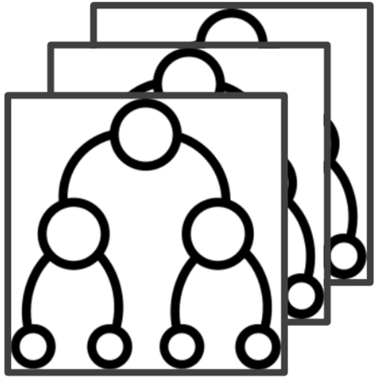
Global Surrogate methods

Idea:

Approximate complex model output with simpler model

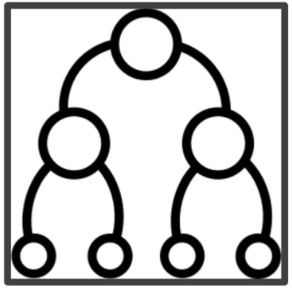
Complex Model



Random Forest Classifier

Predictions: [0,1,0,1,1,0]

Simpler Model



Decision Tree Classifier

Predictions: [0,0,0,1,1,0]

Accuracy: 83.33 % accuracy

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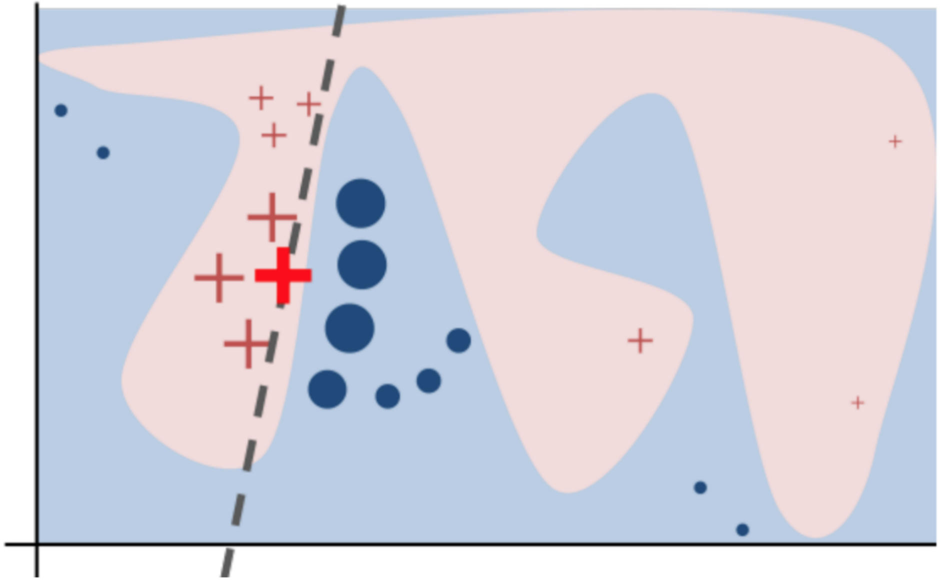
Global Surrogate methods: Steps

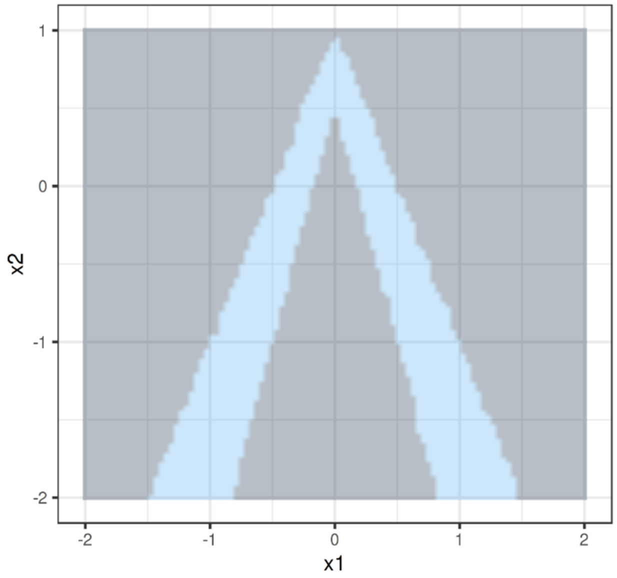
- Interpretable surrogate model that is trained to approximate the predictions of a black box model
- Steps:
  - Get predictions from black box model
  - Select an interpretable model (Linear, DT….)
  - Train interpretable model on original dataset and black box predictions as target
  - Measure performance of surrogate model
  - Interpret the surrogate model

LIME (Local Interpretable Model Agnostic Explanations)

Local interpretation of each prediction for a Black Box Model

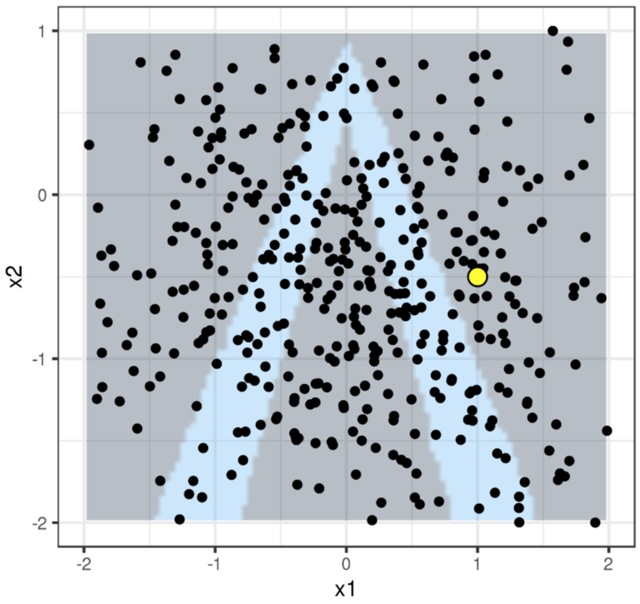


LIME - How does it work?



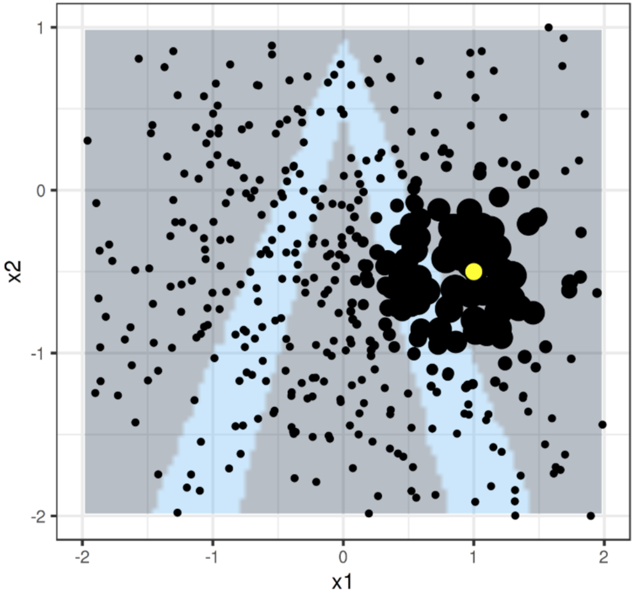
Decision Boundary for a black box model with features x1 and x2

LIME - How does it work?



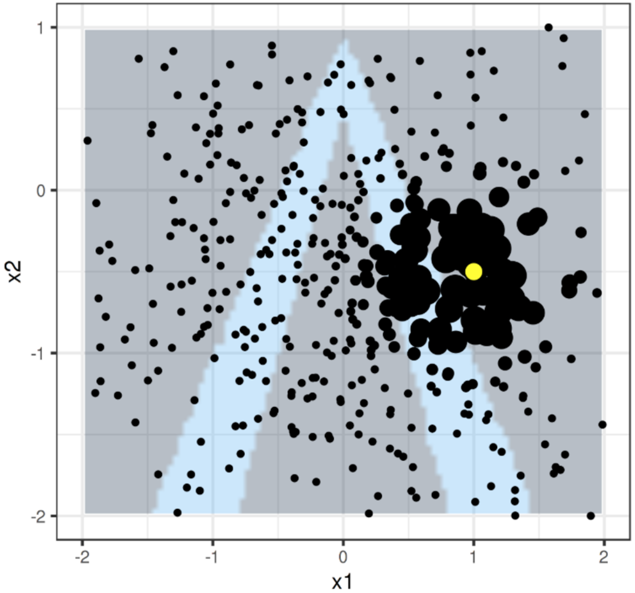
Selected observation (yellow) and data sampled from a normal distribution (black dots)

LIME - How does it work?



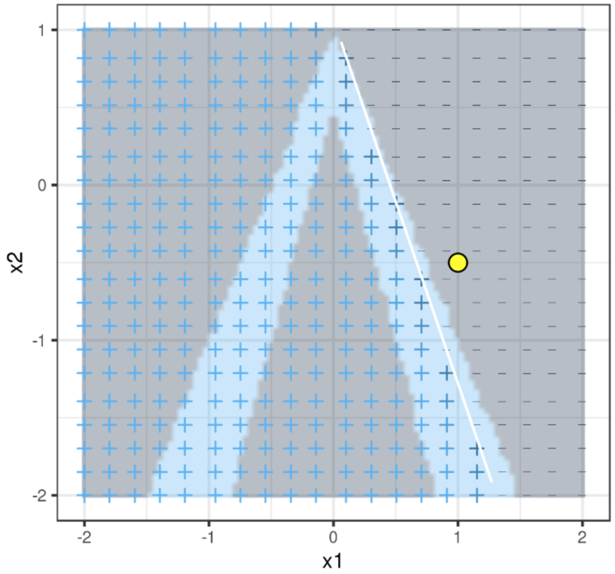
Assign higher weight to points near the our observation

LIME - How does it work?



Train an interpretable model over the fake data generated from the distribution

LIME - How does it work?



The white line marks the new decision boundary for locally learned model

LIME - Let’s Summarise

- Select your instance of interest for which you want to have an explanation of its black box prediction.
- Perturb your dataset and get the black box predictions for these new fake data points.
- Weight the new samples according to their proximity to the instance of interest.
- Train a weighted, interpretable model on the dataset with the variations
- Explain the prediction by interpreting the local model

Thank You!

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