Introduction to Model Interpretability

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CS 224U

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- Why is it important?

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Approaches to Model Interpretability

WHY WE SHOULD CARE

A Typical Machine Learning Example

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  - ML Scientist: Which model features should I use? Does my model perform well?
  - Product Managers: Can I trust/deploy this model? Is it fair for all parties?
  - End User: Why did it give me this prediction?

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  - About making **all** models interpretable
  - About understanding **every single bit** about the model
  - Against developing highly **complex** models
  - About **only** gaining user trust or fairness.
- **Interpretability is the ability to understand the overall consequences of the model and ensuring the things we predict are accurate knowledge aligned with our initial research goal.**

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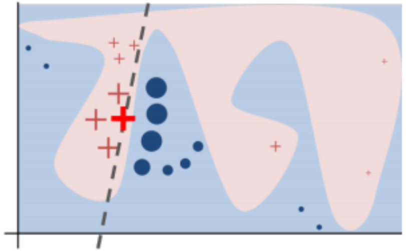
- Helps us identify and mitigate bias, account for context, improve generalization and performance, and is also there for ethical and legal reasons.
- Don’t treat the model as a black box!

Model Agnostic Tactics

HOW THEY HELP



Model Agnostic

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- Ignore internal structure
- Adapt explanation to target user

Local Interpretable Model-Agnostic Explanations (LIME)

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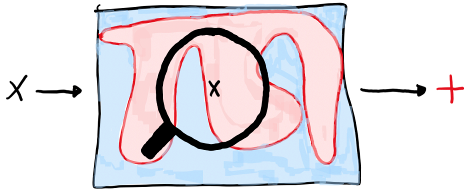
- Global explanations can be too complicated.



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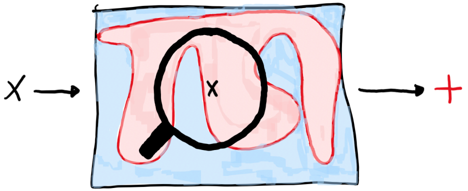
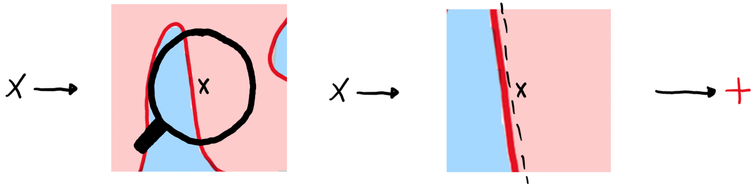


- Zoom in to examine local interpretability



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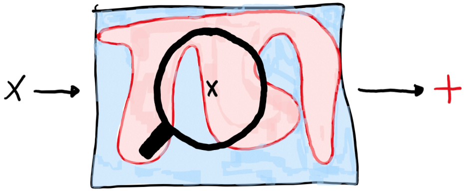

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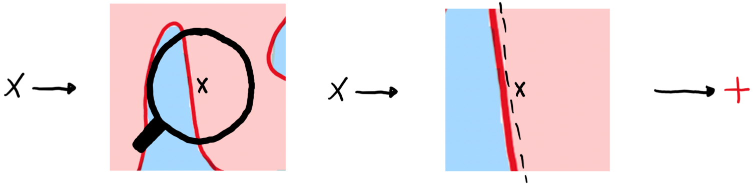

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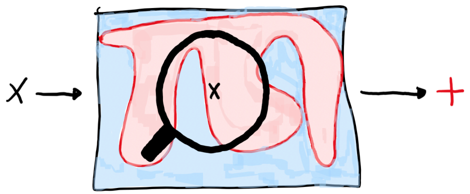

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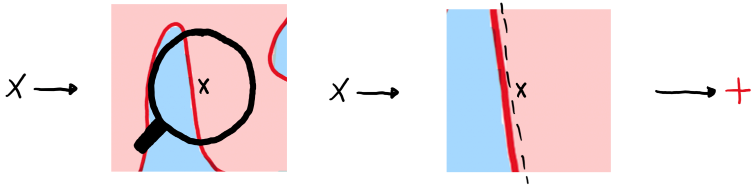

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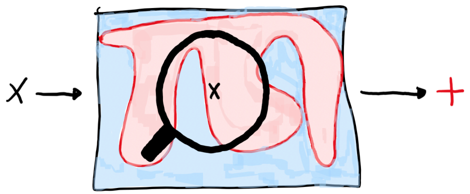

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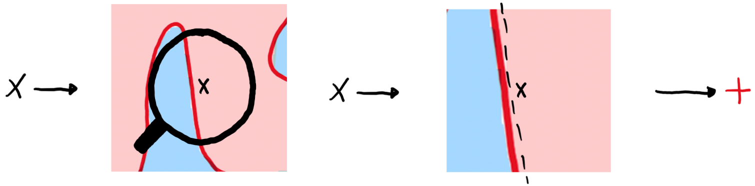
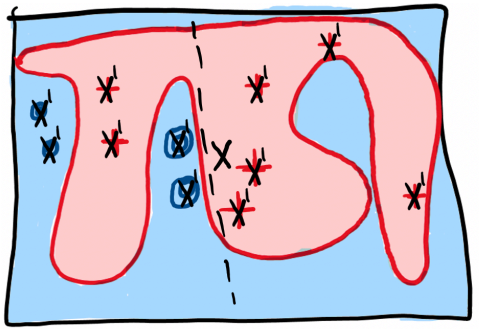


- Summary:
  - Simplify a global model by perturbing input to see how predictions change
  - Approximate underlying model learned on these perturbations

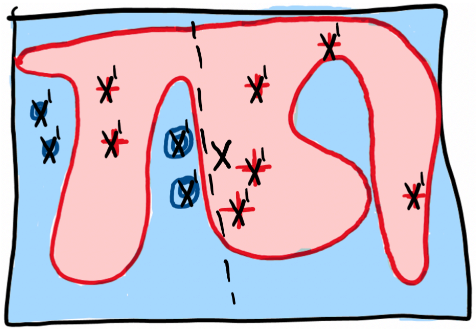
Local Interpretable Model-Agnostic Explanations (LIME)

- Steps:



Local Interpretable Model-Agnostic Explanations (LIME)

- Steps:
  - Sample points around X



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- Steps:
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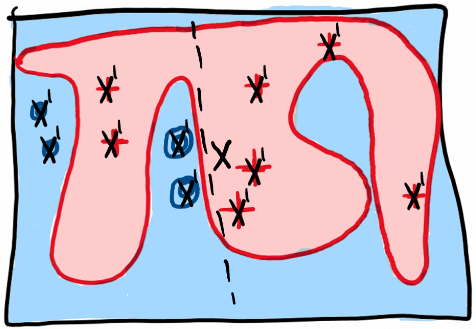

Local Interpretable Model-Agnostic Explanations (LIME)

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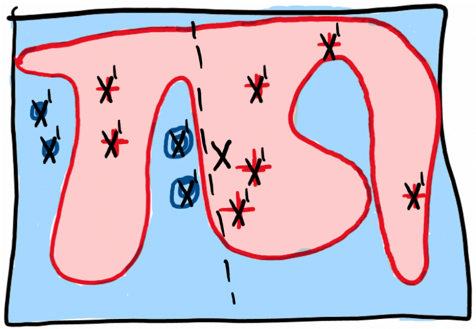

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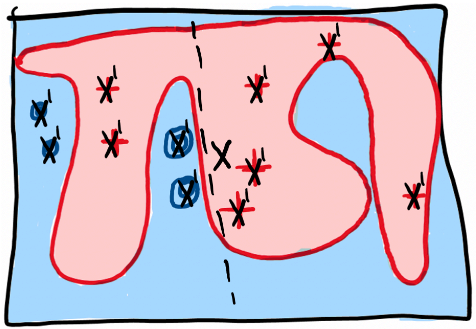

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- Steps:
  - Sample points around X
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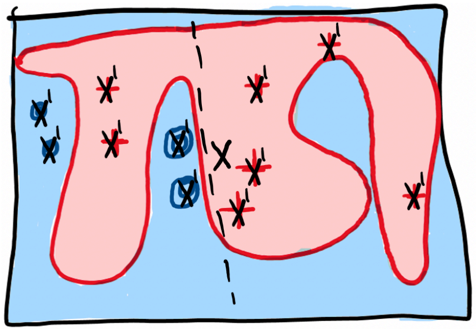
  - Learn a simple model from our weighted samples
  - Utilize simple model for better interpretability!

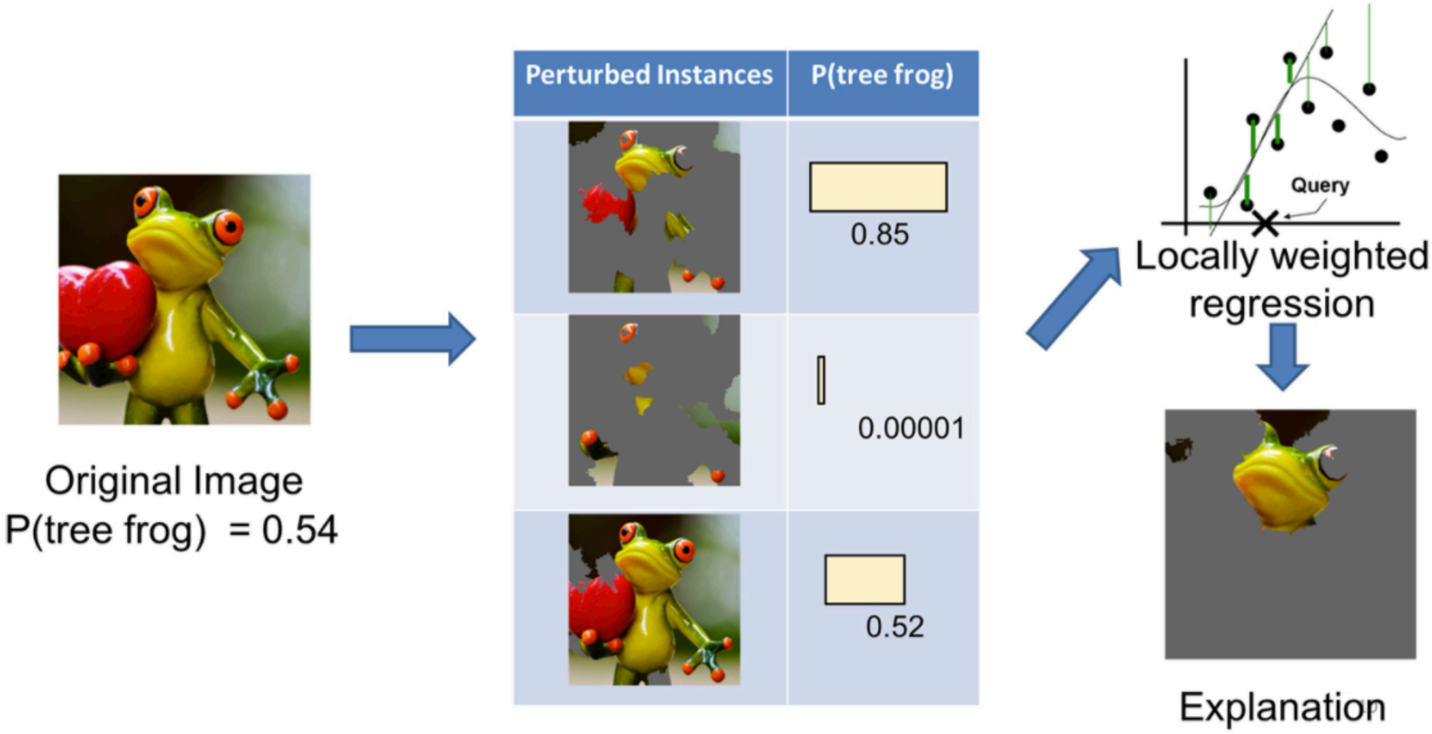


LIME - Images

Original Image

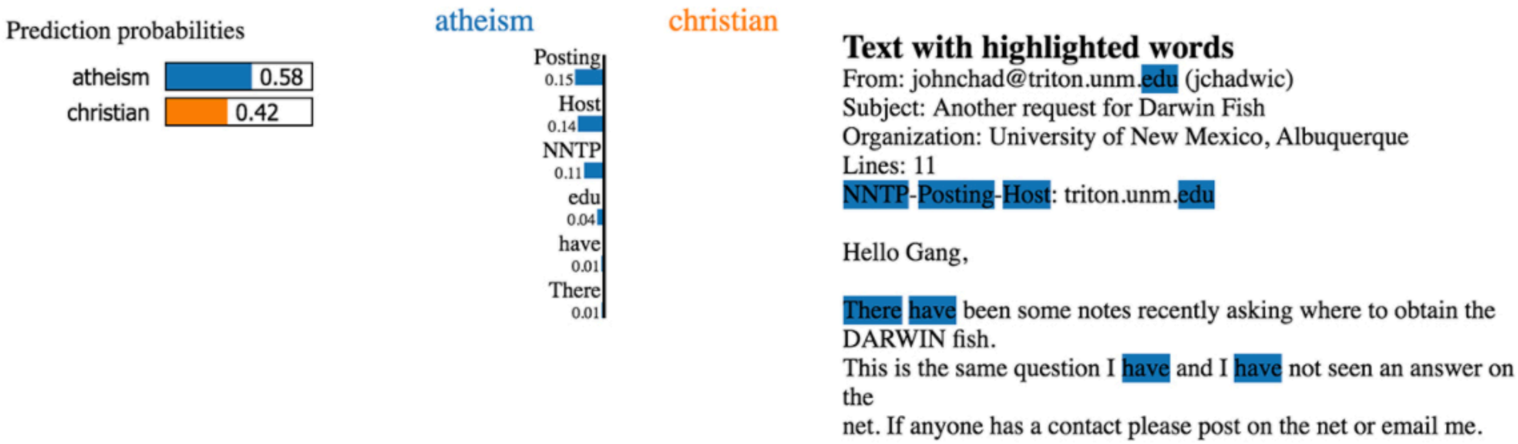
Interpretable Components

LIME - Images


Original Image
P(tree frog) = 0.54
Perturbed Instances
P(tree frog)
0.85
0.00001
0.52
Query
Locally weighted regression
Explanation

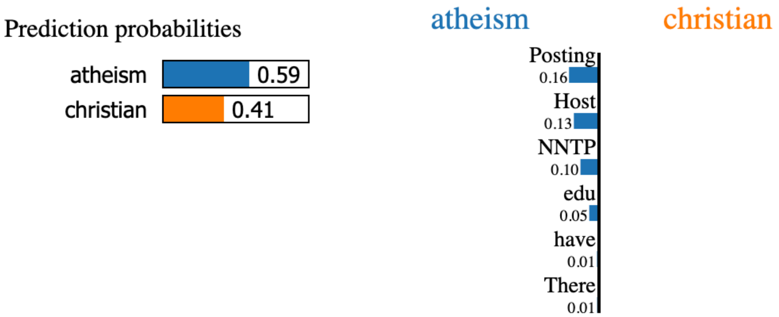
LIME – Text Classification

On 20 newsgroup dataset … what happened?



LIME – Implementation (with simple Random Forest)

```
from lime import lime_text
from lime.lime_text import LimeTextExplainer
from sklearn.pipeline import make_pipeline
c = make_pipeline(vectorizer, rf)
explainer = LimeTextExplainer(class_names=class_names)
exp = explainer.explain_instance(
   newsgroups_test.data[idx],
   c.predict_proba,
   num_features=6)
```



LIME – Drawbacks

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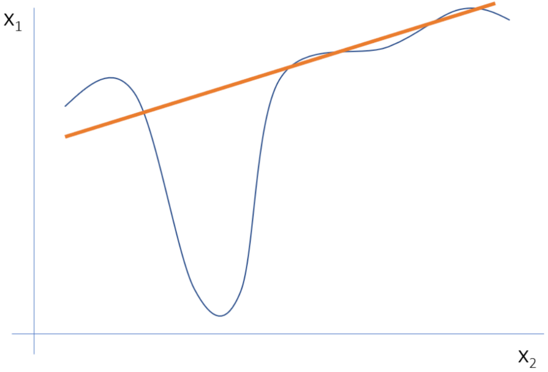
- Linear model approximating local behavior



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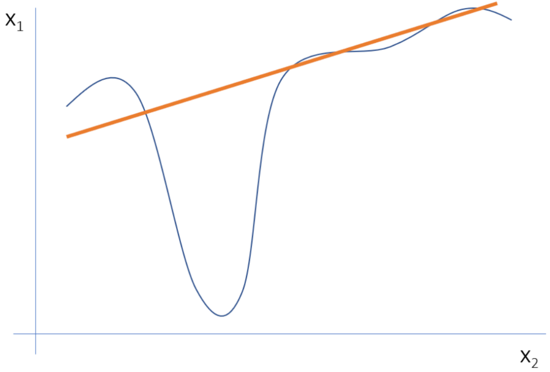

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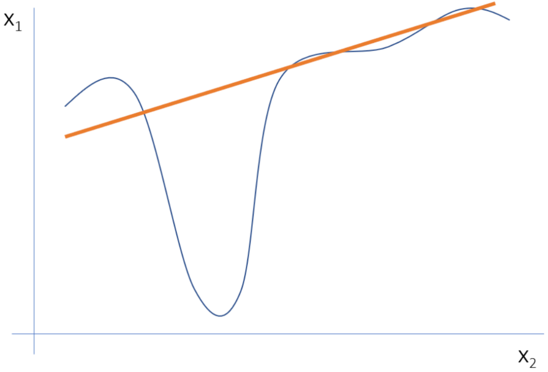
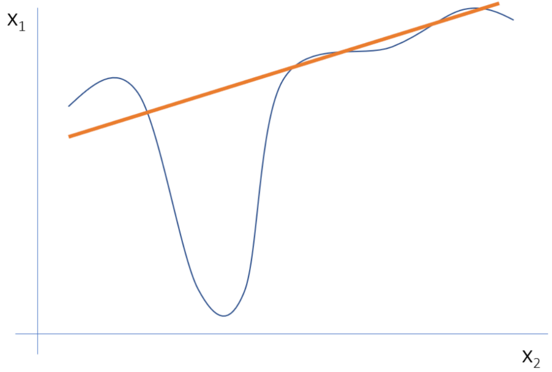


LIME – Drawbacks

- Linear model approximating local behavior
- Perturbations can be very use case specific
- Ideally, drive perturbations by variation in dataset
- Labor/resource intensive when picking better models



Shapley Additive exPlanations (SHAP)

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- Explain output through optimal credit allocation using Shapley values

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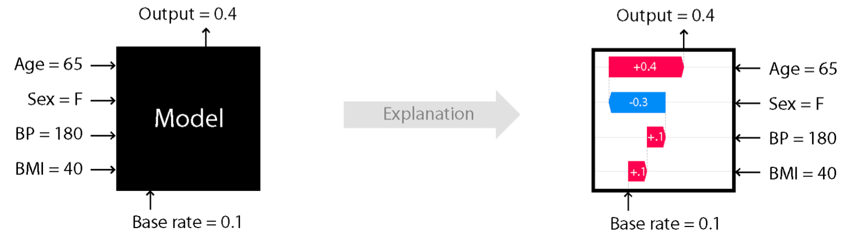
- Explain output through optimal credit allocation using Shapley values
- Allow for both global interpretability (feature contribution) and local interpretability (observation contribution)

SHAP



Shapley Additive exPlanations (SHAP) – Shapley Values

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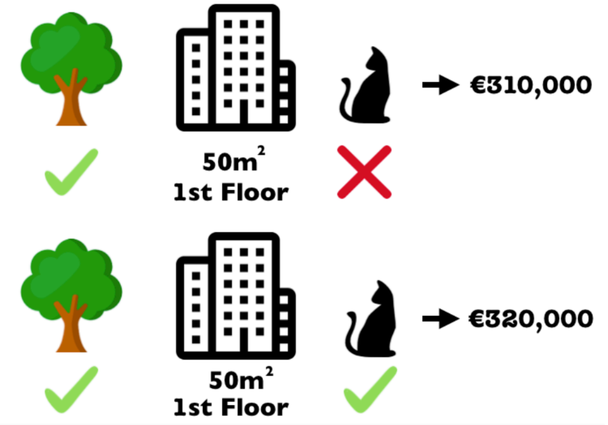
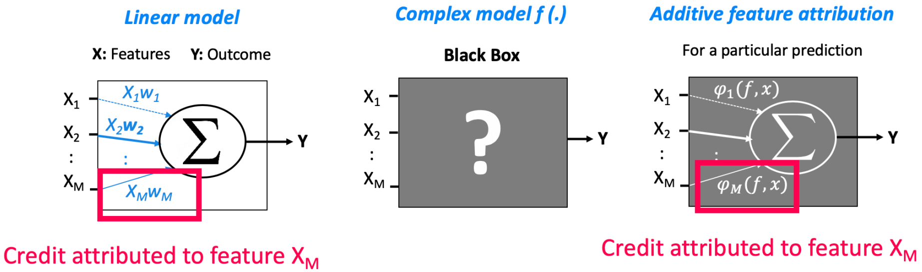
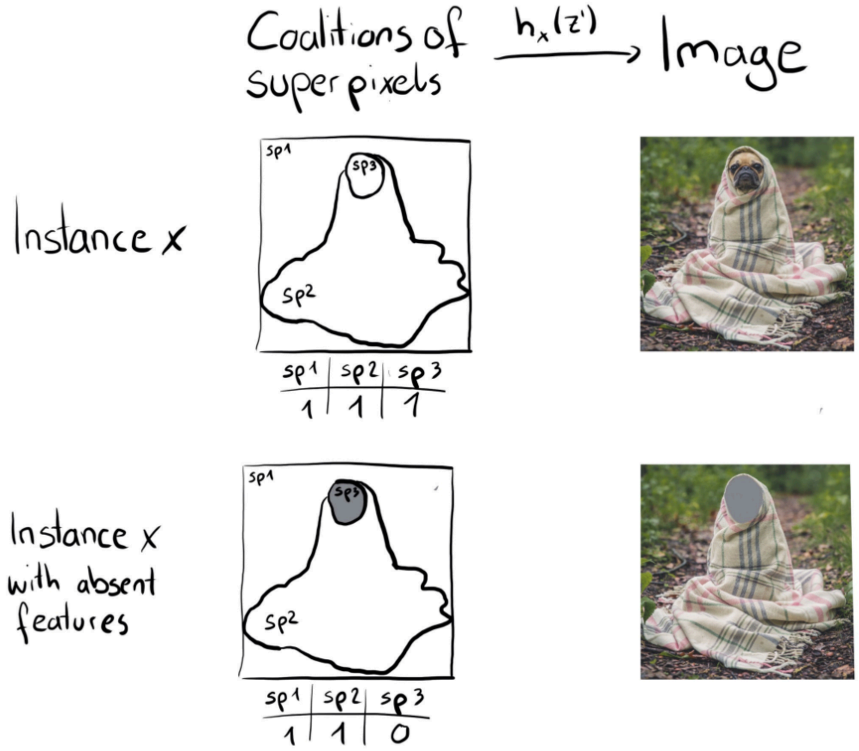
- Shapley value is the average marginal contribution of a feature value across all possible coalitions/orderings! Considers efficiency, symmetry, dummy, and additivity properties.

$$g(x') = \phi_0 + \sum_{j=1}^{M} \phi_j$$

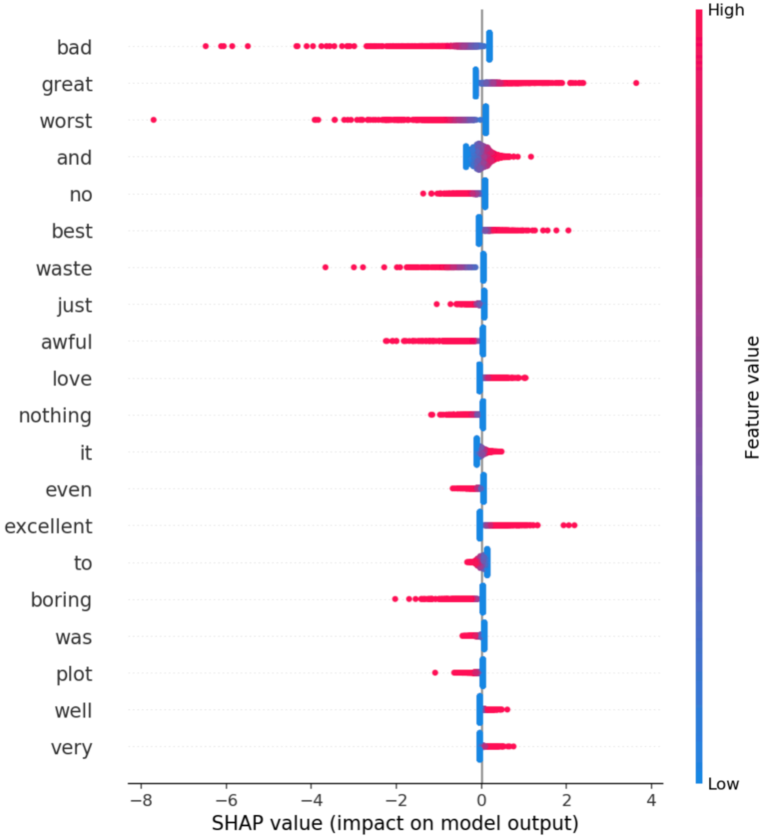




SHAP - Images

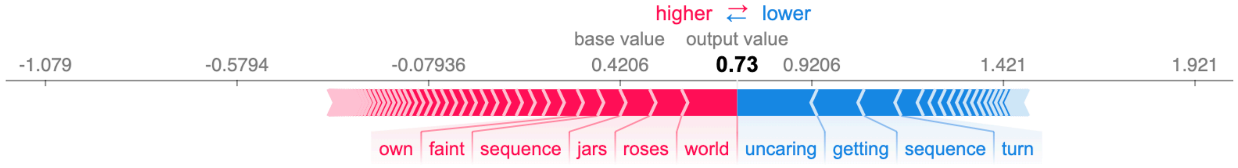

Coalitions of superpixels
$h_x(z')$
Image
Instance x
sp1
sp3
sp2
sp1 | sp2 | sp3
1 | 1 | 1
Instance x with absent features
sp1
sp3
sp2
sp1 | sp2 | sp3
1 | 1 | 0

SHAP – Text Classification



SHAP – Implementation (Keras LSTM Model)

```
import shap
explainer = shap.DeepExplainer(model, x_train[:100])
shap_values = explainer.shap_values(x_test[:10])
shap.initjs()
words = imdb.get_word_index()
num2word = {}
for w in words.keys():
    num2word[words[w]] = w
x_test_words = np.stack([np.array(list(map(lambda x: num2word.get(x,
"NONE"), x_test[i]))) for i in range(10)])
shap.force_plot(explainer.expected_value[0], shap_values[0][0],
x_test_words[0])
```



SHAP – Drawbacks

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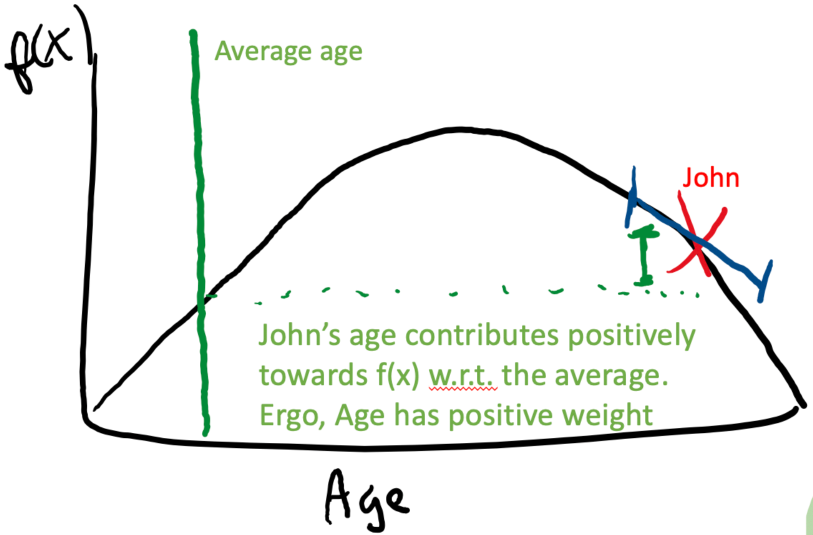
- Can be misinterpreted (don’t identify causality, and don’t break consistency!)
- Direct access to data is necessary

LIME vs SHAP



LIME: weight is local approximation

If you increase age, f(x) goes down
if you decrease it, f(x) goes up
Ergo, Age has negative weight

SHAP: weight is contribution w.r.t baseline

Thank you!

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Works Cited

- Intro to AI Interpretability + Model Agnostic Solutions (Marco Ribeiro)
- Interpretability for Everyone (Been Kim)
- Interpreting ML Models/LIME (Lars Hulstaert)
- SHAP - A unified approach to interpreting model predictions (Scott Lundberg)