Local Interpretability of Machine Learning Models

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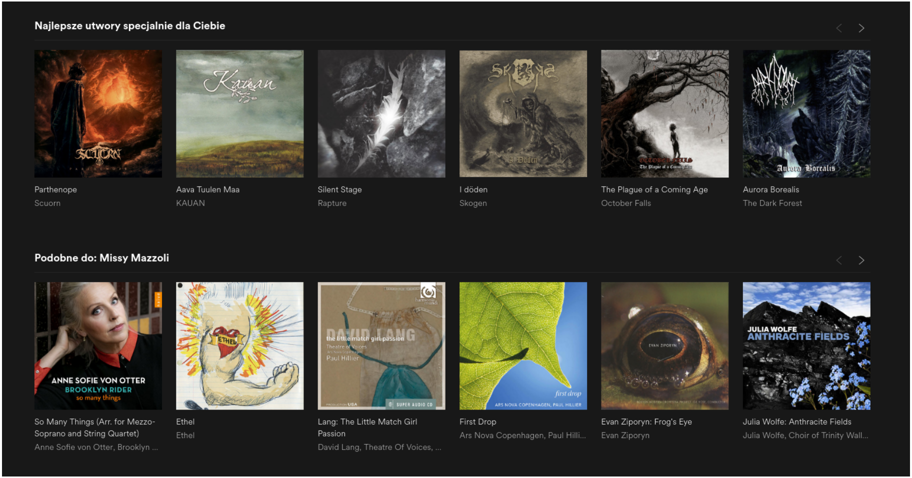
Example


Najlepsze utwory specjalnie dla Ciebie
Parthenope
Scuorn
Aava Tuulen Maa
KAUAN
Silent Stage
Rapture
I döden
Skogen
The Plague of a Coming Age
October Falls
Aurora Borealis
The Dark Forest
Podobne do: Missy Mazzoli
ANNE SOFIE VON OTTER
BROOKLYN RIDER
so many things
So Many Things (Arr. for Mezzo-Soprano and String Quartet)
Anne Sofie von Otter, Brooklyn ...
Ethel
Ethel
the little match girl passion
Paul Hillier
Lang: The Little Match Girl Passion
David Lang, Theatre Of Voices, ...
first drop
ARS NOVA COPENHAGEN, PAUL HILLIER
First Drop
Ars Nova Copenhagen, Paul Hilli...
EVAN ZIPORYN
Evan Ziporyn: Frog's Eye
Evan Ziporyn
JULIA WOLFE
ANTHRACITE FIELDS
Julia Wolfe: Anthracite Fields
Julia Wolfe, Choir of Trinity Wall...

Crucial questions

- Do we **understand** the model?
- Do we **trust** the model?

Possible approaches

Modeling

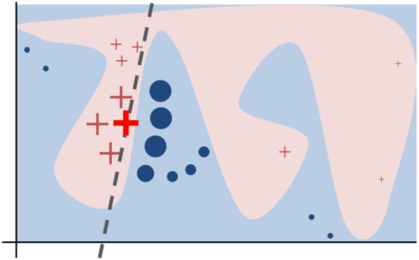
- Interpretable models only
- GAMs
- Surrogate models
- Model-specific explanations (`randomForestExplainer`, `xgboostExplainer`, ...)
- Model-agnostic explanations

Visualization

- Partial dependence plots
- Residual analysis
- Forest floor plots
- Other methods...

Main concepts I

- **interpretable representation**
- **local fidelity**
- **local exploration**



Formulation

- $x \in \mathbb{R}^d$ - instance being explained
- $x' \in \{0,1\}^{d'}$ - interpretable representation
- $g \in G$ - a model that belongs to a class of interpretable models
- $\Omega(g)$ - measure of complexity of g (penalty term)
- $f(x)$ - explained model
- $\pi_x(z)$ - measure of closeness of z and x
- $\mathcal{L}(f, g, \pi_x(z))$ - measure of unfaithfulness of local approximation

LIME explanation $\xi(x)$ is obtained by

$$\xi(x) = \arg\min_{g \in G} \mathcal{L}(f, g, \pi_x(z)) + \Omega(g)$$

LIME: summary

LIME addresses

- **understanding** issue by approximating the complex model with an interpretable model,
- **trust** issue using accompanying sp-LIME algorithm, which picks representative instances and their explanations.

live: Motivation & Explanation

Why?

- LIME for regression problems
- Model visualization in aid of LIME

How?

- Create dataset for local exploration by perturbing the explained instance.
- Use original variables as interpretable inputs.
- Optional variable selection.
- Provide tools for model visualization.
- Focus on interpretable models easy to visualize.

Some good news

- The method finds the right local model.
- The method is pretty stable (similar results for different *fake* datasets).
- White box predictions are close to black box predictions at and around chosen instance.
- General framework: Shapley values.

Case study

- `live` package: `https://www.github.com/MI2DataLab/live`
  - `sample_locally` → `add_predictions`
  - `fit_explanation` → `plot_explanation`
- Wine quality data.

```
# A tibble: 6 x 12
  fixed_acidity volatile_acidity citric_acid residual_sugar chlorides free_sulfur_dioxide total_sulfur_dioxide
          <dbl>            <dbl>       <dbl>          <dbl>     <dbl>               <dbl>                <dbl>
1           7.4             0.70        0.00            1.9     0.076                  11                   34
2           7.8             0.88        0.00            2.6     0.098                  25                   67
3           7.8             0.76        0.04            2.3     0.092                  15                   54
4          11.2             0.28        0.56            1.9     0.075                  17                   60
5           7.4             0.66        0.00            1.8     0.075                  13                   40
6           7.9             0.60        0.06            1.6     0.069                  15                   59
# ... with 5 more variables: density <dbl>, pH <dbl>, sulphates <dbl>, alcohol <dbl>, quality <int>
```

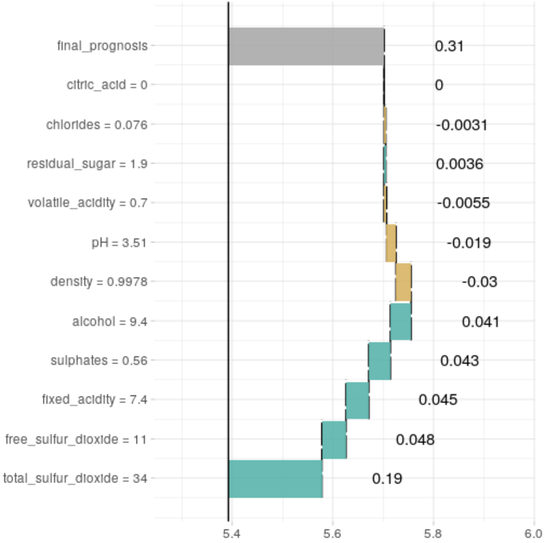
Case study

```
similar <- sample_locally(data = winequality_red,
                          explained_instance = winequality_red[5, ],
                          explained_var = "quality",
                          size = 100,
                          standardise = TRUE)
similar1 <- add_predictions(winequality_red, similar,
                            "regr.randomForest")
similar2 <- add_predictions(winequality_red, similar, "regr.svm")
trained <- fit_explanation(live_object = similar1,
                           white_box = "regr.lm",
                           selection = TRUE)
plot_explanation(trained,
                 regr_plot_type = "forestplot",
                 explained_instance = winequality_red[5, ])
```

Case study

Variable	Observed	Estimate	Lower	Upper
sulphates	0.56	0.08	0.06	0.09
citric_acid	0	0.06	0.05	0.07
chlorides	0.08	-0.04	-0.05	-0.03
density	1	-0.03	-0.04	-0.02

Case study


final_prognosis
citric_acid = 0
chlorides = 0.076
residual_sugar = 1.9
volatile_acidity = 0.7
pH = 3.51
density = 0.9978
alcohol = 9.4
sulphates = 0.56
fixed_acidity = 7.4
free_sulfur_dioxide = 11
total_sulfur_dioxide = 34
0.31
0
-0.0031
0.0036
-0.0055
-0.019
-0.03
0.041
0.043
0.045
0.048
0.19
5.4
5.6
5.8
6.0

Challenges

- LIME in high dimensional setting,
- optimal way of generating *fake* dataset,
- measures of fit,
- visualizing shrinkage methods...

Acknowledgements

Uniwersytet Wrocławski

MI

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