Measuring and optimizing machine learning interpretability

Christoph Molnar, Giuseppe Casalicchio, Bernd Bischl

LMU Munich

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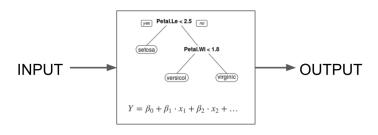
Black Box Problem



Problem: Tradeoff interpretability and performance

Use only interpretable models (e.g. linear model)!

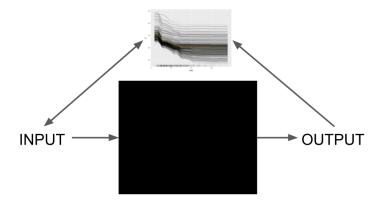
 \Rightarrow Pay with loss in performance.



Problem: Tradeoff interpretability and performance

Just use post-hoc interpretation methods (e.g. feature importance)!

 \Rightarrow Works better for less complex models.



What's interpretability anyway?



We propose measures of model complexity

Measure model complexity in a model-agnostic way: number of features, interaction strength, main effect complexity

- ⇒ Allows model comparision
- ⇒ Allows direct optimization for interpretability
- \Rightarrow Makes claims of interpretability more explicit ("Model A uses less features than B and has less interactions")

Functional Decomposition

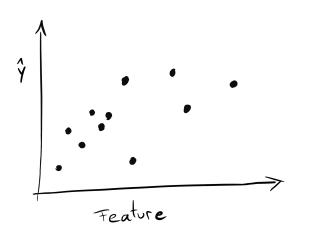
$$f(x) = \overbrace{f_0}^{\text{Intercept}} + \underbrace{\sum_{j=1}^{p} f_j(x_j)}^{\text{1st order effects}} + \underbrace{\sum_{j\neq k}^{\text{2nd order effects}} f_{jk}(x_j, x_k) + \ldots + \underbrace{f_{1, \dots, p}(x_1, \dots, x_p)}_{\text{p-th order effect}}$$

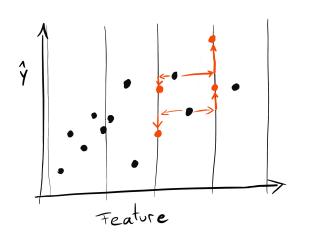
Functional Decomposition

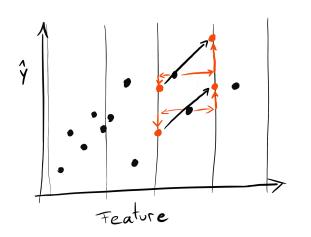
$$f(x) = \overbrace{f_0}^{ ext{Intercept}} + \sum_{j=1}^{ ext{Ist order effects}} \underbrace{\sum_{S \subseteq \{1, \dots, p\}, |S| \ge 2}^{ ext{Higher order effects}}}_{S \subseteq \{1, \dots, p\}, |S| \ge 2}$$

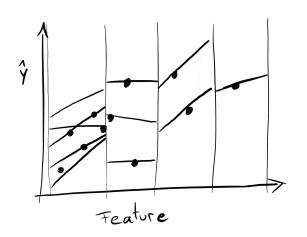
Functional Decomposition

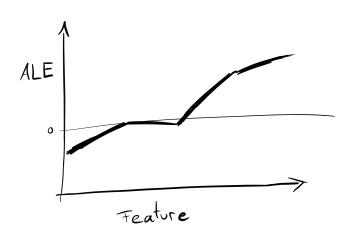
$$f(x) = f_0 + \sum_{j=1}^{p} \overbrace{f_j(x_j)}^{\text{How complex?}} + \underbrace{IA(x)}_{IA(x)}$$
How many feature used?





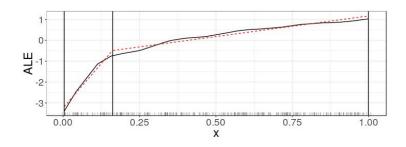






Main effect complexity

- Approximate ALE plot with linear segments
- ► Count number of non-zero coefficients
- ► Average over all features, weight with variance



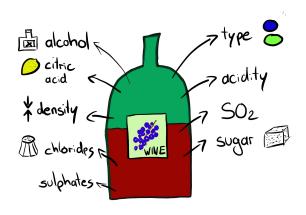
Interaction Strength

Measure main effect model with proportion of error explained:

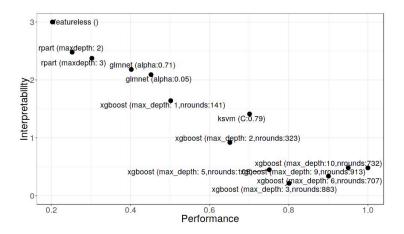
Interaction Strength =
$$\frac{\mathbb{E}(L(\hat{f}, f_0 + \sum_{j=1}^p f_j)}{\mathbb{E}(L(\hat{f}, c))}$$

Application: Multi-Objective Optimization

- Predict wine quality from phsicochemical properties
- Minimize MAE, number of features, interaction strength, main effect complexity
- Search across different model classes and hyperparameter settings



Application: Multi-Objective Optimization



Application: Multi-Objective Optimization

	xgboost	ksvm (C:0.79)	xgboost	rpart
	(max_depth:	(,	(max_depth:	(maxdepth:
	9,nrounds:913)		1,nrounds:141)	3)
MAE	0.47	0.53	0.57	0.61
NF	11	11	11	3
IA	0.64	0.27	0.02	0.14
MEC	4.12	1.99	2.90	1.81
fixed.acidity				
volatile.acidity			~	
citric.acid				
residual.sugar				
chlorides				
free.sulfur.dioxide			$\overline{}$	
total.sulfur.dioxide				
density				
рН				
sulphates				
alcohol				

Table 3. A selection of 4 models from the Pareto optimal set. From left to right, the models with best MAE, best MAE when $MEC \le 2$, best MAE when $IA = \le 0.1$, best MAE with $NF \le 7$.

Interested in interpretable machine learning?

More on interpretable machine learning in my book http://christophm.github.io/interpretable-ml-book/.

