Exploring Tools for Interpretable Machine Learning

Dr. Juan Orduz

PyData Global 2021





Outline

Introduction

Data Set

Models Fit

Model Explainability

Model Specific

Beta Coefficients and Weight Effects

Tree ensembles

Model Agnostic

PDP and ICE Plots

Permutation Importance

SHAP

References

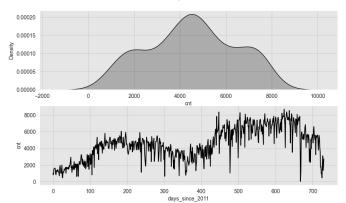




Target Variable - cnt: Daily Bike Rents

	season	yr	mnth	holida	weekday	workingday	weathersit	temp	hum	windspeed	cnt	days_since_2011
0	SPRING	2011	JAN	NO HOLIDA	' SAT	NO WORKING DAY	MISTY	8.175849	80.5833	10.749882	985	0
1	SPRING	2011	JAN	NO HOLIDA	' SUN	NO WORKING DAY	MISTY	9.083466	69.6087	16.652113	801	
	SPRING	2011	JAN	NO HOLIDA	' MON	WORKING DAY	GOOD	1.229108	43.7273	16.636703	1349	
3	SPRING	2011	JAN	NO HOLIDA	' TUE	WORKING DAY	GOOD	1.400000	59.0435	10.739832	1562	
4	SPRING	2011	JAN	NO HOLIDA	/ WED	WORKING DAY	GOOD	2.666979	43.6957	12.522300	1600	

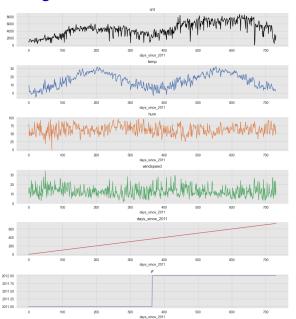
cnt: Target Variable







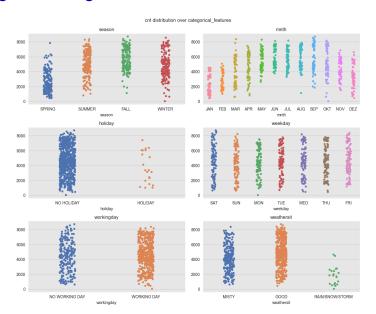
Continuous Regressors







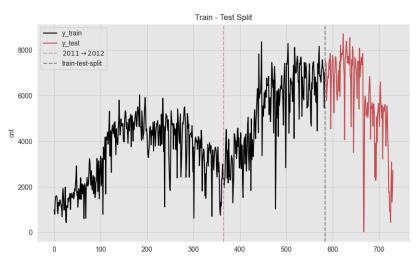
Categorical Regressors







Train-Test Split



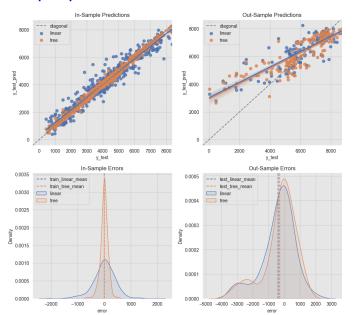




Models



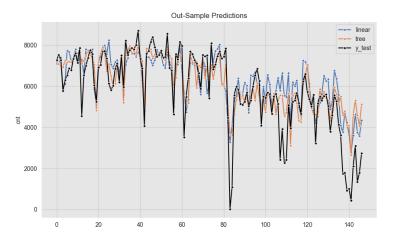
Out of sample performance - Erros Distribution







Out of sample performance - Predictions







β coefficeients

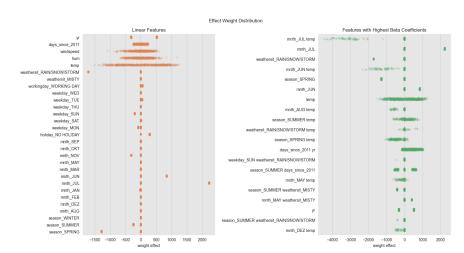
$$y = \beta_0 + \beta_1 x_1 + \dots + \beta_p x_p + \varepsilon$$
, where $\varepsilon \sim N(0, \sigma^2)$

	linear_features	coef_	abs_coef_
0	mnth_JUL temp	-2305.096894	2305.096894
	mnth_JUL	2227.672335	2227.672335
	weathersit_RAIN/SNOW/STORM	-1710.469071	1710.469071
	mnth_JUN temp	-1299.644413	1299.644413
	season_SPRING	-1279.629779	1279.629779
	mnth_JUN	845.229031	845.229031
	temp	646.609622	646.609622
	mnth_AUG temp	-523.011653	523.011653
	season_SUMMER temp	489.319256	489.319256
	weathersit_RAIN/SNOW/STORM temp	-482.660271	482.660271
10	season_SPRING temp	465.512410	465.512410
11	days_since_2011 yr	465.079169	465.079169
12	weekday_SUN weathersit_RAIN/SNOW/STORM	-462.286059	462.286059
13	season_SUMMER days_since_2011	454.137278	454.137278
14	mnth_MAY temp	-445.268148	445.268148
15	season_SUMMER weathersit_MISTY	-408.809531	408.809531
16	mnth_MAY weathersit_MISTY	404.790954	404.790954
17		403.199142	403.199142
18	${\tt season_SUMMER\ weathersit_RAIN/SNOW/STORM}$	-394.157306	394.157306
19	mnth_DEZ temp	363.222114	363.222114





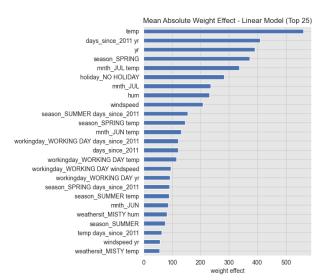
Weight Effects $\beta_i x_i$







Weight Effects Importance $w_i = \frac{1}{n} \sum_{i=1}^{n} |\beta_i x_i|$







Weight Effects: Temperature (z-transform)

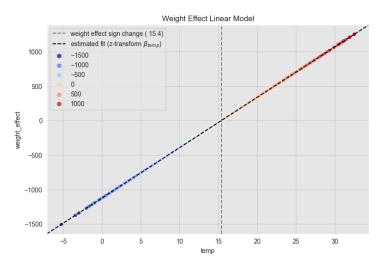


Figure: This plot just shows the effect of the linear term *temp* and not the interactions.





Weight Effects: Interatctions

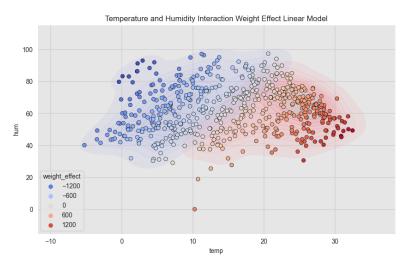
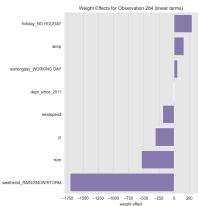


Figure: We can visualize the interaction between temp and hum by computing the total weight effect as $\beta_{temp} x_{temp} + \beta_{hum} x_{hum} + \beta_{temp \times hum} x_{temp} x_{hum}$.



Explaining Individual Predictions

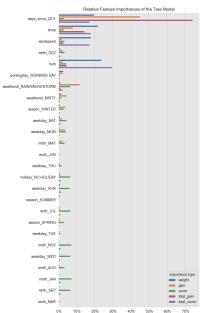








Feature Importance Metrics: XGBoost



relative importance





Partial Dependence Plot (PDP) & Individual Conditional Expectation (ICE) ([1, Section 5.1])

Let x_S be the features for which the partial dependence function should be plotted and x_C be other features used in the machine learning model. One can estimate the *dependence function as*

$$\hat{f}_{x_S}(x_S) = \frac{1}{n} \sum_{i=1}^n \hat{f}(x_S, x_C^i)$$

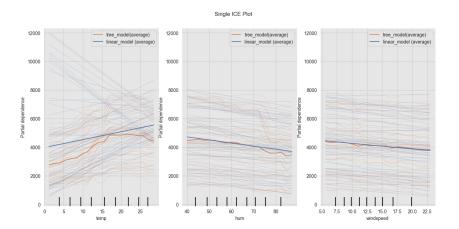
where \hat{f} is the model prediction function, x_C^i are actual feature values (not in S) and n is the number points.

Similar to a PDP, an individual conditional expectation (ICE) plot shows one line per instance. That is, for each instance in $\{(x_S^i, x_C^i)\}_{i=1}^n$, we plot \hat{f}_S as a function of x_S^i while leaving x_C^i fixed.



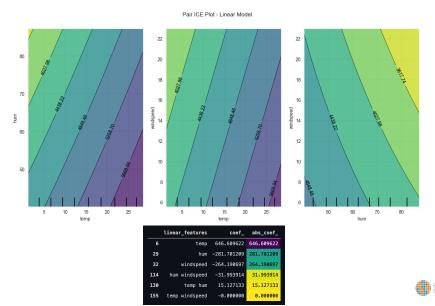


PDP & ICE Examples (1D)





PDP & ICE Examples (2D)



Permutation Importance

Measures the increase in the prediction error of the model after we permuted the feature's values, which breaks the relationship between the feature and the true outcome ([1, Section 5.5]).

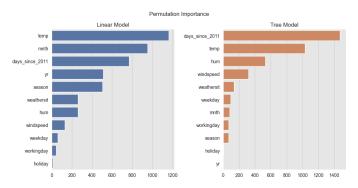
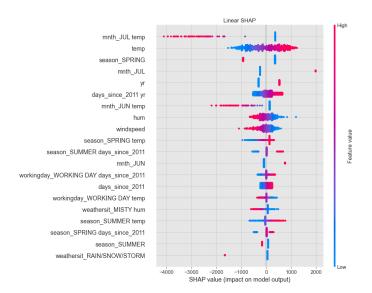


Figure: The permutation importance for these two models have *days_since_2011* and *temp* on their top 3 ranking, which partially explain the trend and seasonality components respectively (see [1, Figure 5.30]).



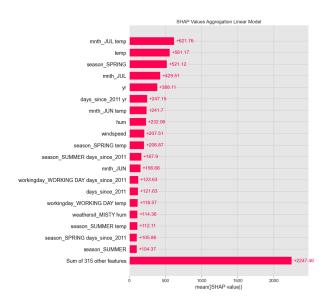
SHAP Values: Linear Model







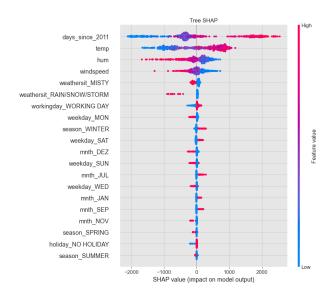
Mean Abs SHAP Values: Linear Model







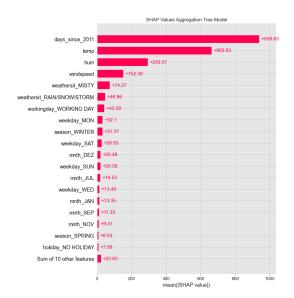
SHAP Values: XGBoost







Mean Abs SHAP Values: XGBoost







SHAP Values: Temperature

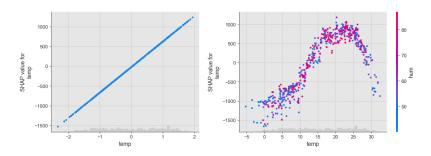


Figure: ...

SHAP Values: Observation 284

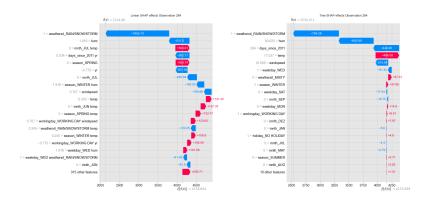


Figure: ...





References I

Christoph Molnar.
 Interpretable Machine Learning.
 2019.

https://christophm.github.io/interpretable-ml-book/.



Thank You!

Contact

- ▶ **()** github.com/juanitorduz
- ▶ y juanitorduz
- ▶ juanitorduz@gmail.com





