



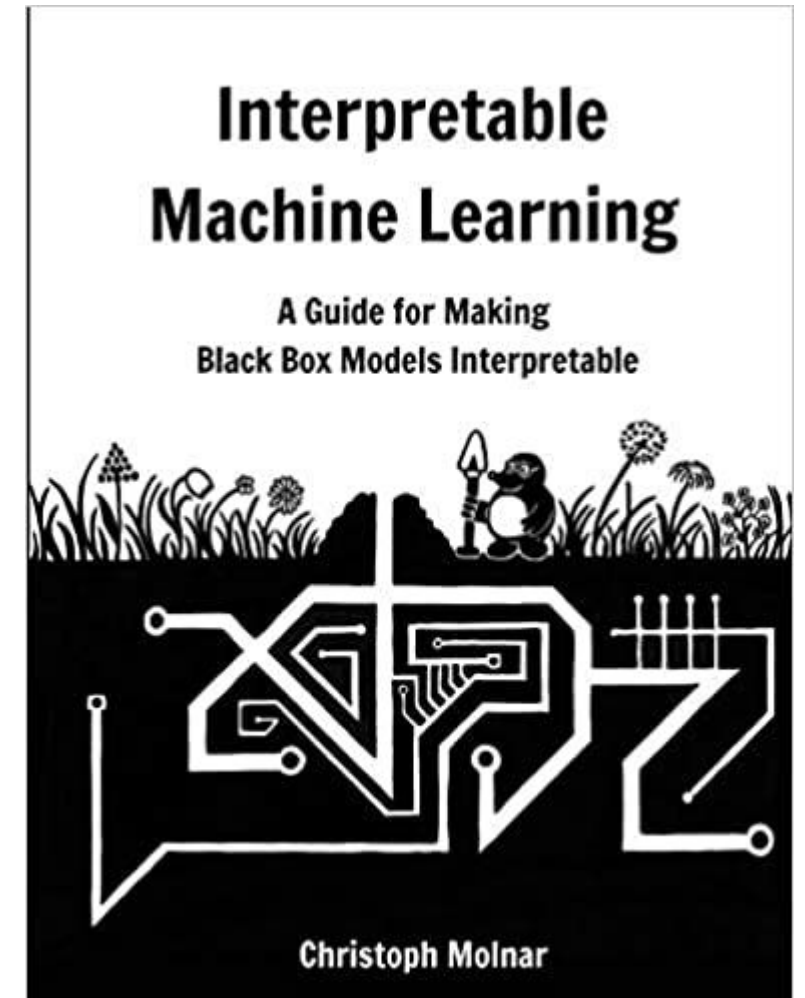
Nikolay Manchev
Principal Data Scientist for EMEA
Domino Data Lab
[@nikolaymanchev](#)

Interpreting Machine Learning Models

16 JULY 2020

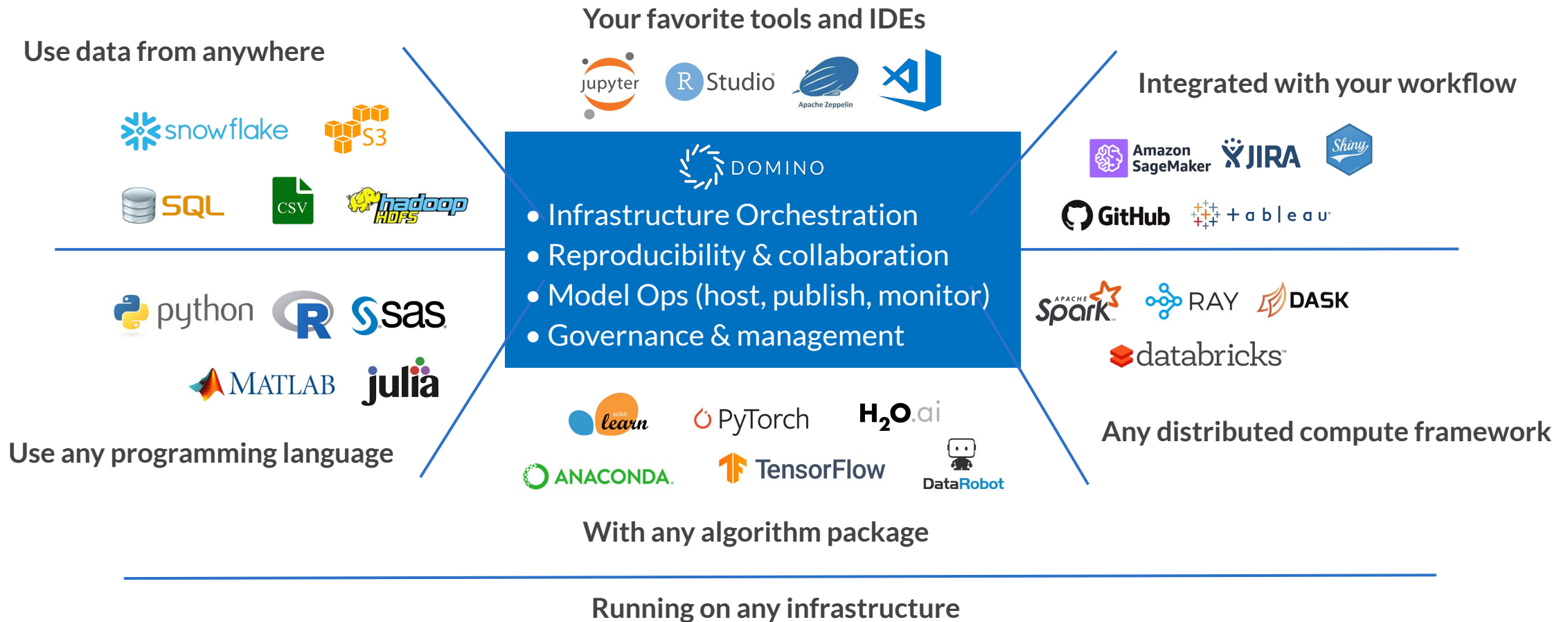
Housekeeping

- Moving to virtual events until the Covid-19 situation is resolved
- Next event - 27th August
- I need your help
 - Speakers
 - Topics
- The slide deck will be available on github
<https://github.com/nmanchev/LondonDSML>
- To get in touch with me use **@nikolaymanchev**
- Prize



Domino is “The Center of the ML Ecosystem”

The gateway to data science infrastructure and the system of record for work





Nikolay Manchev
Principal Data Scientist for EMEA
Domino Data Lab
@nikolaymanchev

Interpreting Machine Learning Models

16 JULY 2020

Why Interpretable Models

- No hard-coded rules
 - Difficult to explain to the business
 - Justifying decisions
- Biased models can have devastating effects
 - Predicting potential criminals

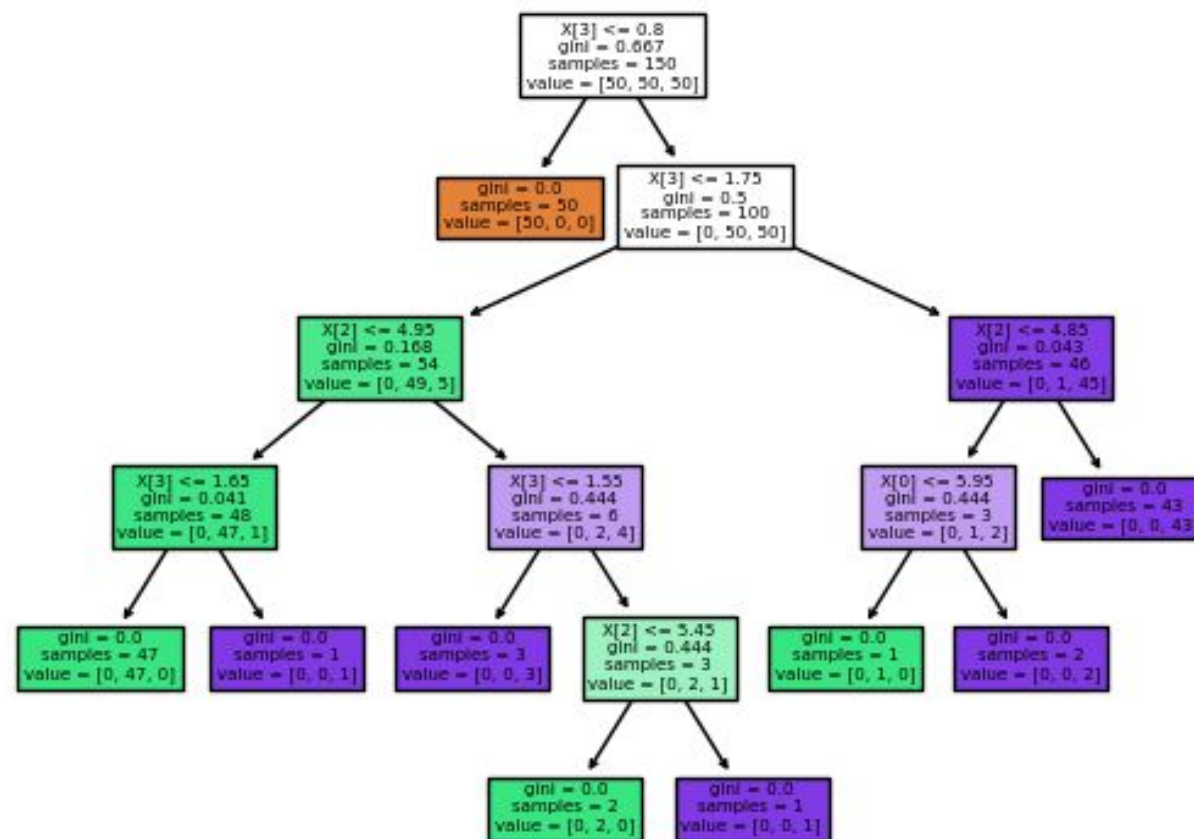
<https://weaponsofmathdestructionbook.com/>



<https://xkcd.com/1838>

Interpretable Models

- Linear Regression
- Logistic Regression
- GLM
- Decision Trees
- Naive Bayes



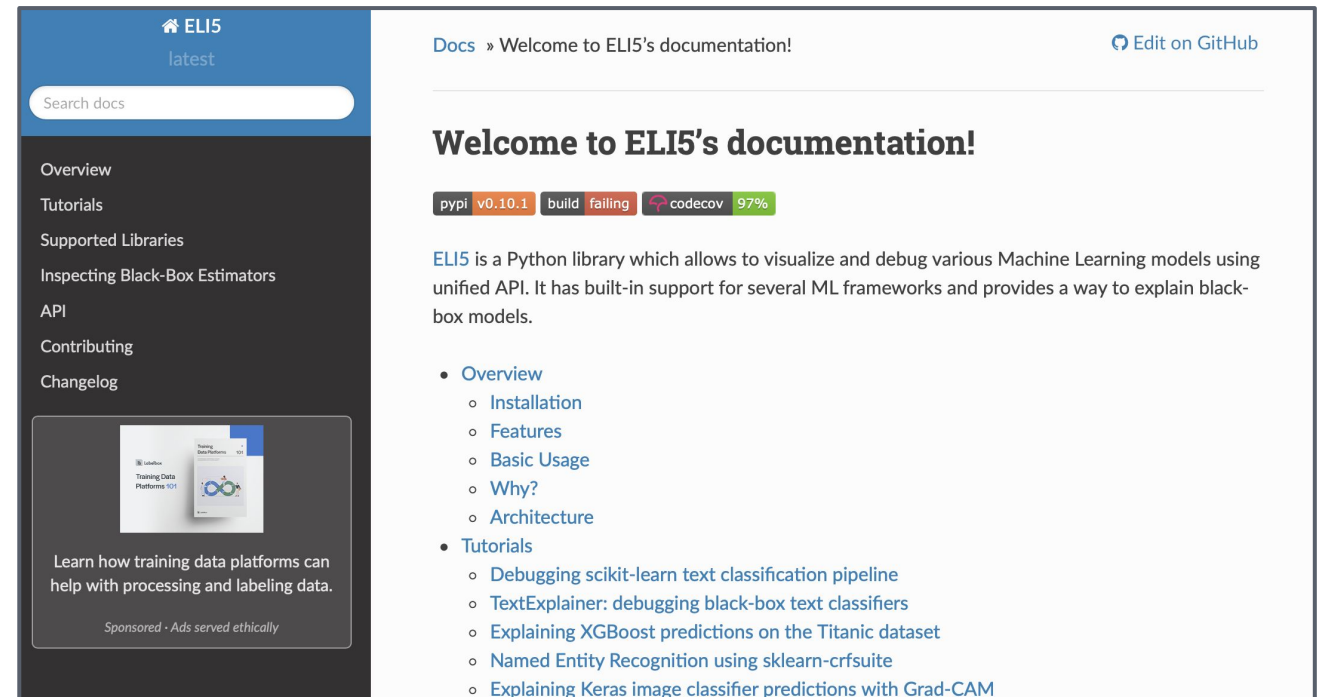
[Scikit-learn official documentation](https://scikit-learn.org/stable/modules/decision_trees.html), Decision Trees, Section 1.10

Ensemble Models (e.g. XGBoost)

- The **what vs. why** tradeoff:
 - The sole purpose of using an ensemble is to increase predictive performance
 - Will interpreting an average of models going to answer anything?
 - `n_estimators=100` by default in XGBoost
- There are still things we can do
 - How important are the individual features?
 - Gain - average gain across all splits the feature is used in.
 - Cover - average coverage across all splits the feature is used in
 - Weight - number of times a feature is used to split the data across all trees
 - Examining individual predictions

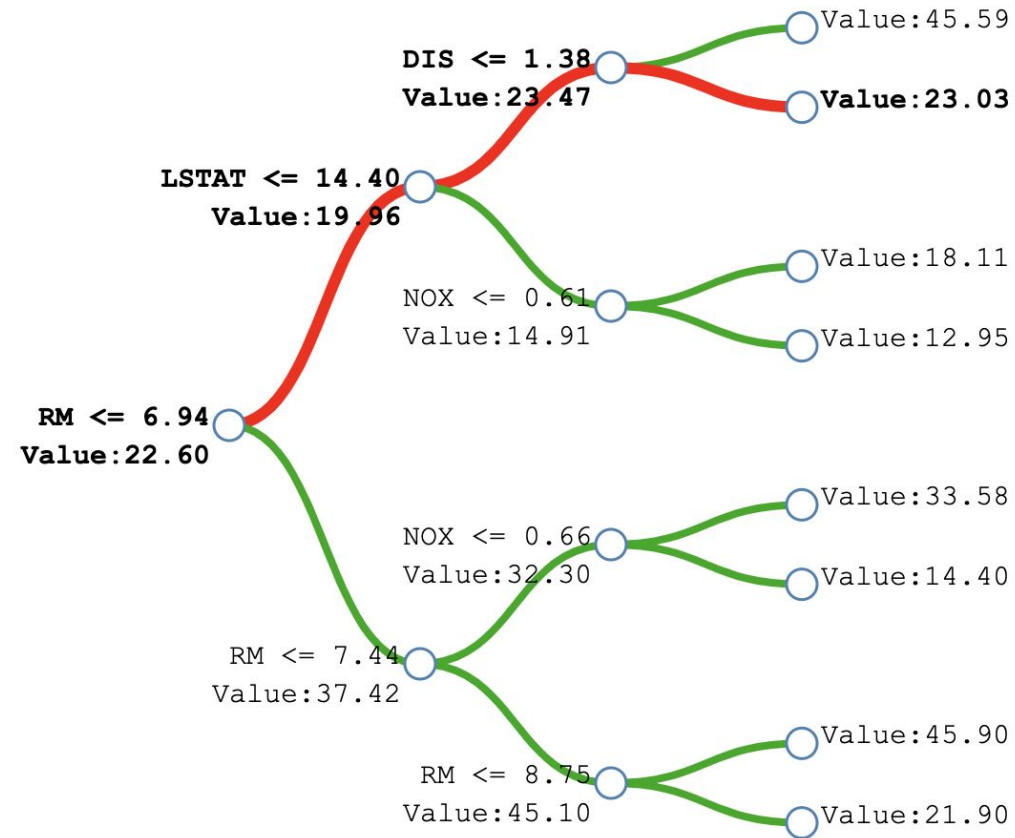
ELI5

- ELI5 is a Python library which allows to visualize and debug various Machine Learning models
- Built-in support for several ML frameworks and provides a way to explain black-box models.
 - Scikit-learn
 - XGBoost
 - lightning
 - Keras
 - ...



The screenshot shows the ELI5 documentation website. The header is blue with the ELI5 logo and 'latest' version. A search bar is present. The left sidebar lists navigation links: Overview, Tutorials, Supported Libraries, Inspecting Black-Box Estimators, API, Contributing, and Changelog. The main content area has a 'Welcome to ELI5's documentation!' heading, followed by version and build status (pypi v0.10.1, build failing, codecov 97%). A paragraph describes ELI5 as a Python library for visualizing and debugging ML models. A list of links includes Overview (Installation, Features, Basic Usage, Why?, Architecture) and Tutorials (Debugging scikit-learn text classification pipeline, TextExplainer: debugging black-box text classifiers, Explaining XGBoost predictions on the Titanic dataset, Named Entity Recognition using sklearn-crfsuite, Explaining Keras image classifier predictions with Grad-CAM). A footer note says 'Sponsored - Ads served ethically'.

ELI5's interpretation algorithm



Prediction: 23.03 \approx 22.60 (trainset mean) - 2.64(loss from RM) + 3.52(gain from LSTAT) - 0.44(loss from DIS)

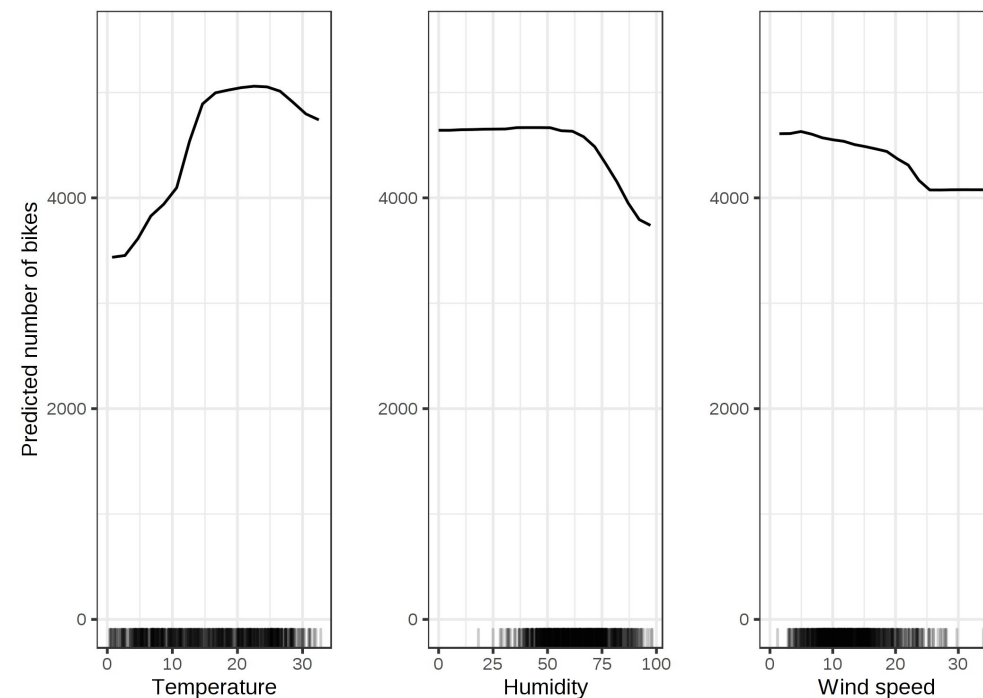
Partial Dependence Plot

- Model agnostic method
- Shows the marginal effect one or two features have on the predicted outcome
- Shows the dependence between the target and a set of "target" features, marginalizing over the values of all other features
- The target features set (S) is usually limited to 2

$$X = [x_s, x_c] \in \mathbb{R}^{n \times p}, y \in \mathbb{R}$$

$$\hat{y} = f(x) + \epsilon$$

$$\hat{f}_s(x) = \frac{1}{n} \sum_{i=1}^n \hat{f}(x, x_c), x \in x_s$$



PDPs for the bicycle count prediction model, [Interpretable Machine Learning](#), Christoph Molnar, Section 5.1

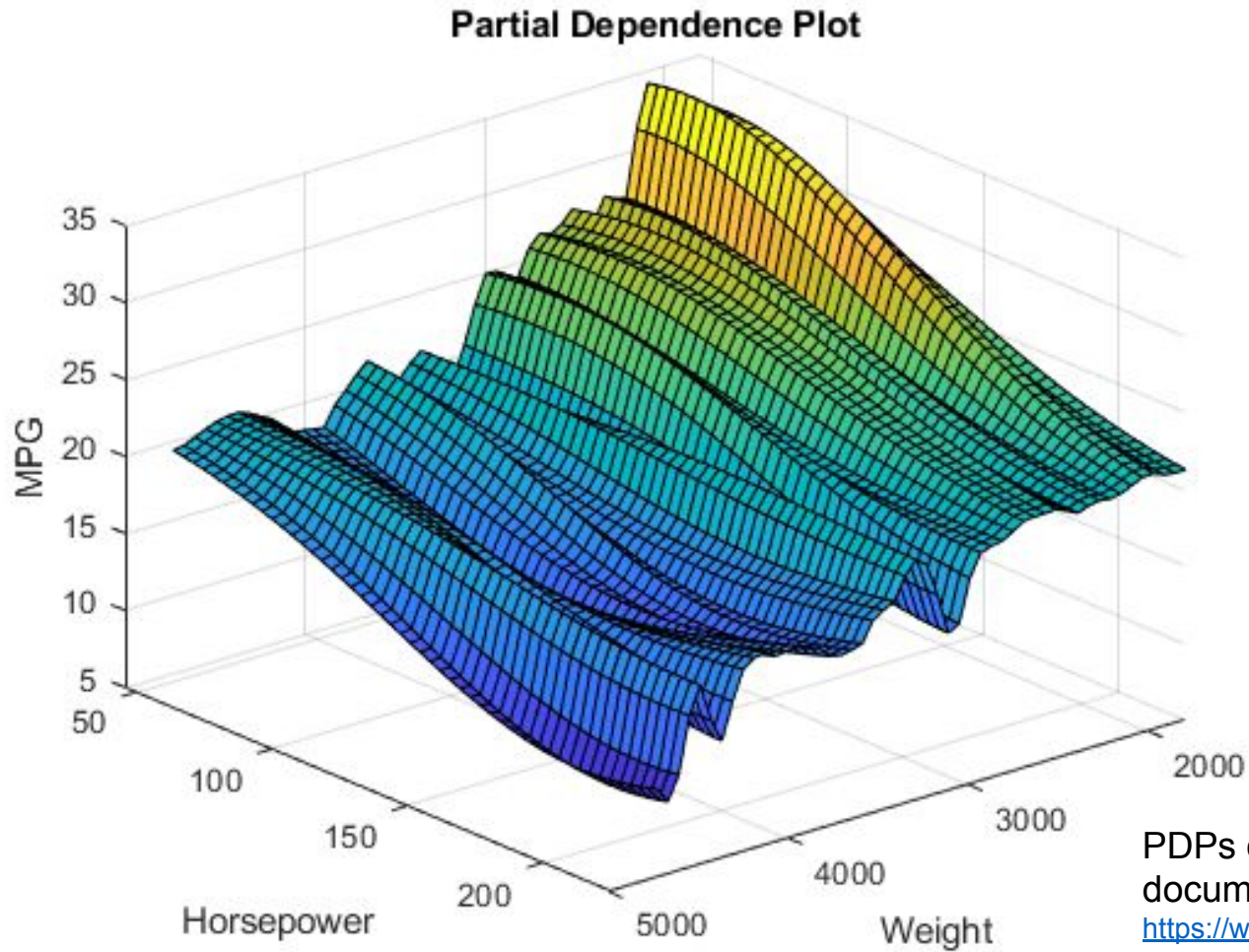
Skater

- Unified framework to enable Model Interpretation for all forms of model
- Supports local and operationalised models

Scope of Interpretation	Algorithms	
Global Interpretation	Model agnostic Feature Importance	
Global Interpretation	Model agnostic Partial Dependence Plots	
Local Interpretation	Local Interpretable Model Explanation(LIME)	
Local Interpretation	DNNs	<ul style="list-style-type: none">• Layer-wise Relevance Propagation (e-LRP): image• Integrated Gradient: image and text
Global and Local Interpretation	<ul style="list-style-type: none">• Scalable Bayesian Rule Lists• Tree Surrogates	

[Skater documentation](#), Overview, Sep 2018, visited 5/2020

PDP on AutoMPG

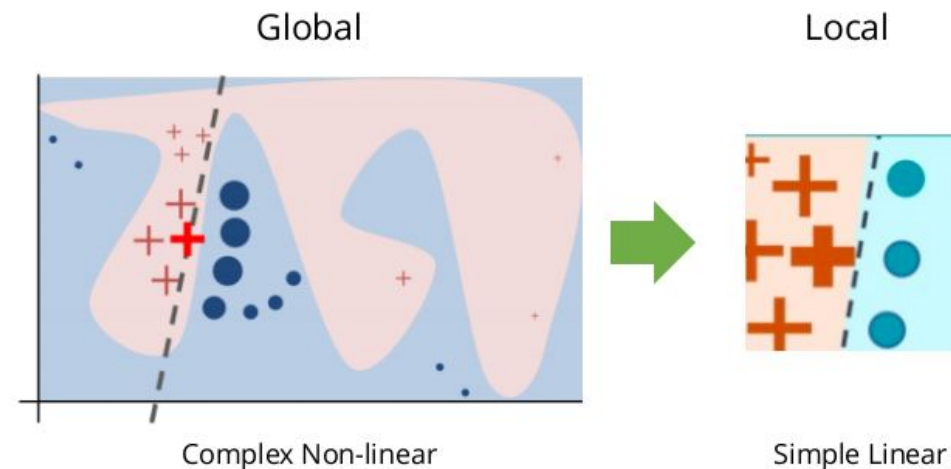


PDPs on the carsmall data set, MATLAB documentation,
<https://www.mathworks.com/help/stats/regressiontree.plotpartialdependence.html>

Local Surrogate (LIME)

- Used to explain individual predictions of black box models*
- Highlights
 - Generate a new dataset consisting of permuted samples and their predictions
 - Train an interpretable model, weighted by the proximity of the sampled instances to the instance of interest

$$\text{explanation}(x) = \arg \min_{g \in G} L(f, g, \pi_x) + \Omega(g)$$



[Interpretability part 3: opening the black box with LIME and SHAP](#), Manu Joseph, KDnuggets

* Ribeiro, Marco Tulio, Sameer Singh, and Carlos Guestrin. "Why should I trust you?: Explaining the predictions of any classifier." Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining. ACM (2016).

<https://www.meetup.com/London-Data-Science-and-Machine-Learning>



LONDON data science
& machine Learning