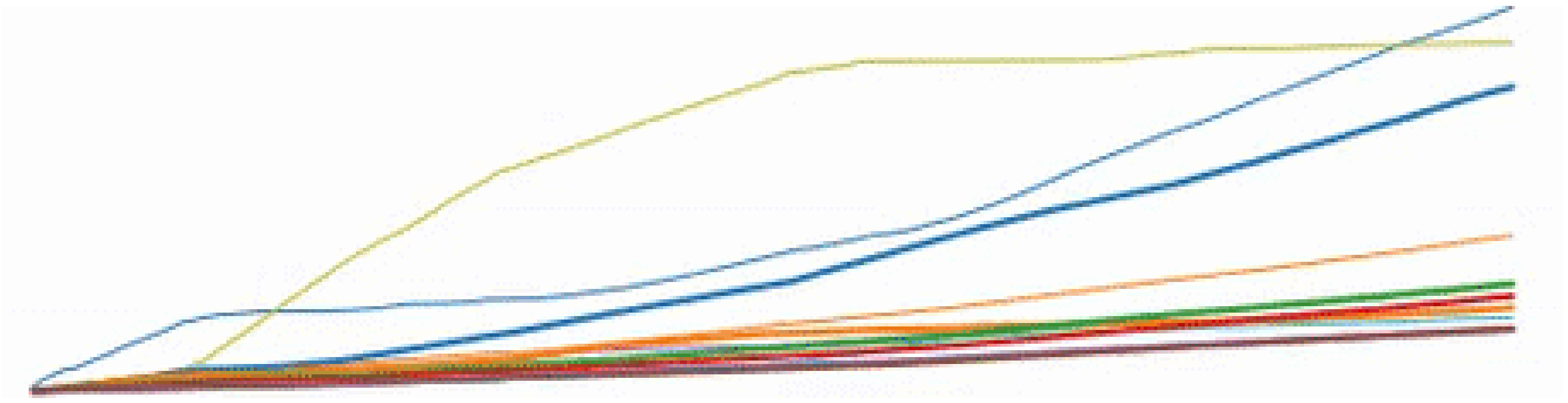
Explainable Artificial Intelligence



Approaches to Robust Online Explanations

August 2021

Outline

- Introduction
  - Motivation
  - Properties
- Experiments
- Results
- (Outlook)

Introduction: Motivation

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- Data streams
  - Noise, Concept drift
  - Retraining of explained model

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- Inconsistent explanations
- Example:
  - At time: t
    - Transient model state
    - Loan not approved with explanation e
  - At time: t + N
    - Loan not approved with explanation e‘ != e
    - e.g. Applicant increased expenses, but transient model state passed

Introduction: Properties

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- Concentration on Approaches:
  - (Explained) Model agnostic
  - Handle Post-hoc explanations
  - Explanations = Feature attributions
- Model attributions from weights as ground truth

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- Desired properties
  - Local faithfulness
  - Global faithfulness
  - Efficiency
  - Stability

Approaches

- Local Explainers
  - LIME
  - SHAP

$$a_t = l(x_t, f(x_t), X)$$

  - X is baseline

Approaches

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- Global Explainers
  - FIRES
    - Feature scores used as Feature attributions
    - Importance + Uncertainty

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$$a_t = FIRES(x_t, f(x_t))$$

  - Weighted Gaussian Explainer
    - Outputs linearly dependent on attributions

$$P(y_t | x_t, a_t) = \mathcal{N}(y_t; {x_t}^T a_t, \Lambda)$$

    - Mean of posterior

Approaches: Combination of Local and Global Explainers

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  1. FIRES → Model distribution
  2. Sample N Models
  3. Local explainer → Explain predictions of N models
     1. LIME or SHAP
  4. Aggregate explanations (e.g. Mean of explanations)

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- Weighted Local and Global Explainers

$$a_t = \frac{w_l \cdot l(x_t, f(x_t)) + w_g \cdot g(x_t, f(x_t))}{w_l + w_g}$$

Experiments

- xEvaluator
  - Environment for experimentation with explanations and data streams

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- Datasets:
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- Ground truth:
  - Explained model weights

Desired Properties

Evaluation Metrics

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Local faithfulness

Evaluation Metrics

$$LF_{t+1} = LF_t + \left| \frac{a_{t+1}}{\Sigma_i |a_{t+1_i}|} - \frac{g_{t+1}}{\Sigma_i |g_{t+1_i}|} \right|$$

Desired Properties	Evaluation Metrics
Local faithfulness	$LF_{t+1} = LF_t + \left\| \frac{a_{t+1}}{\Sigma_i \|a_{t+1_i}\|} - \frac{g_{t+1}}{\Sigma_i \|g_{t+1_i}\|} \right\|$
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Stability	$S_{t+1} = S_t + \left\| \frac{a_{t+1}}{\Sigma_i \|a_{t+1_i}\|} - \frac{a_t}{\Sigma_i \|a_{t_i}\|} \right\|$

Results: Time and Stability

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- Average over all data sets

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	Explainer	Time (ms)
1.	FIRES	0.87
2.	WeightedGaussian	2.34
3.	LIME	8.00
4.	LIME+FIRES	8.95
5.	SHAP	9.56
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7.	LIME-Ensemble	115.92
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- Ensemble stabilizes SHAP

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Results: Local Faithfulness vs Stability

Better

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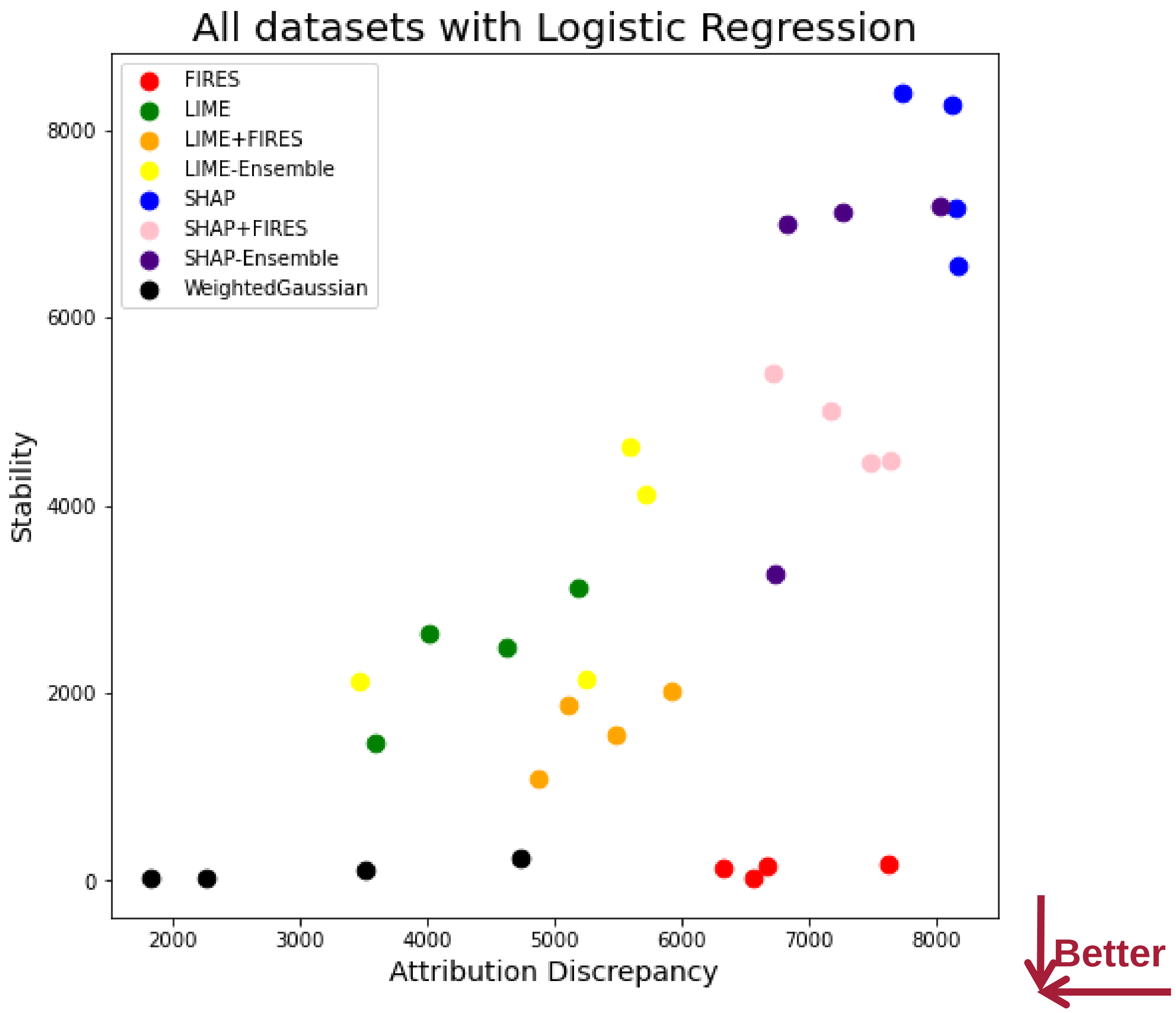

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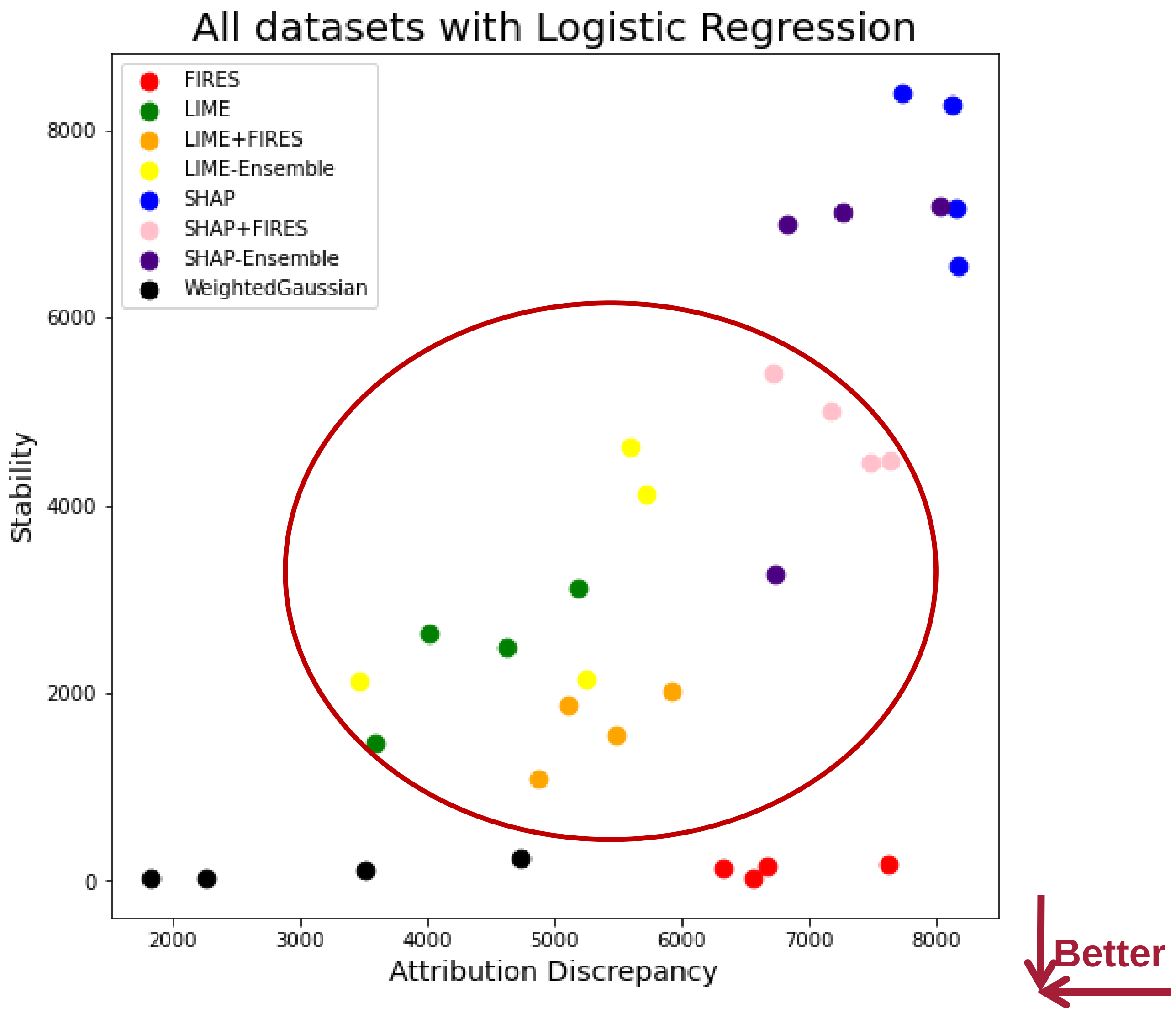

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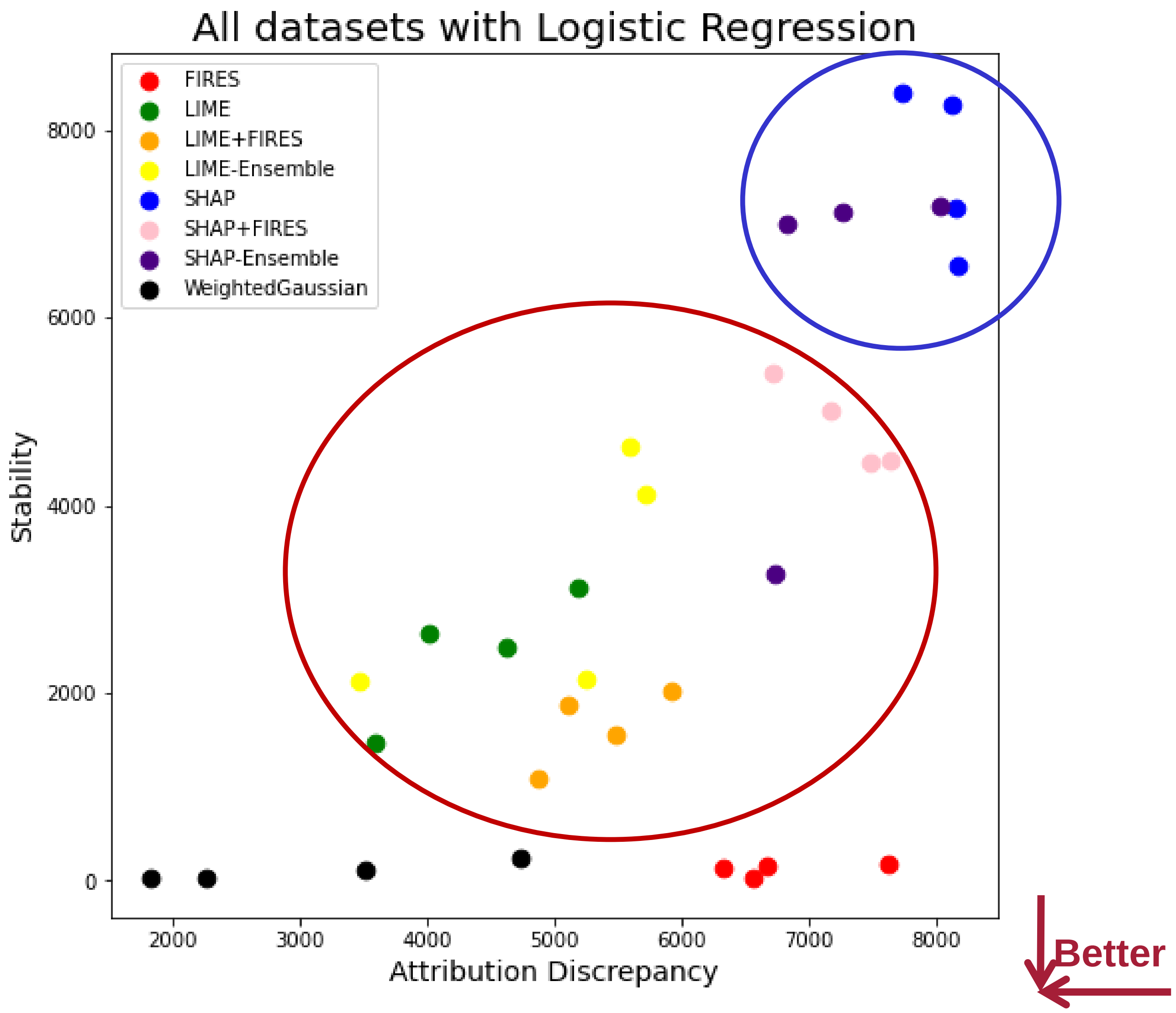

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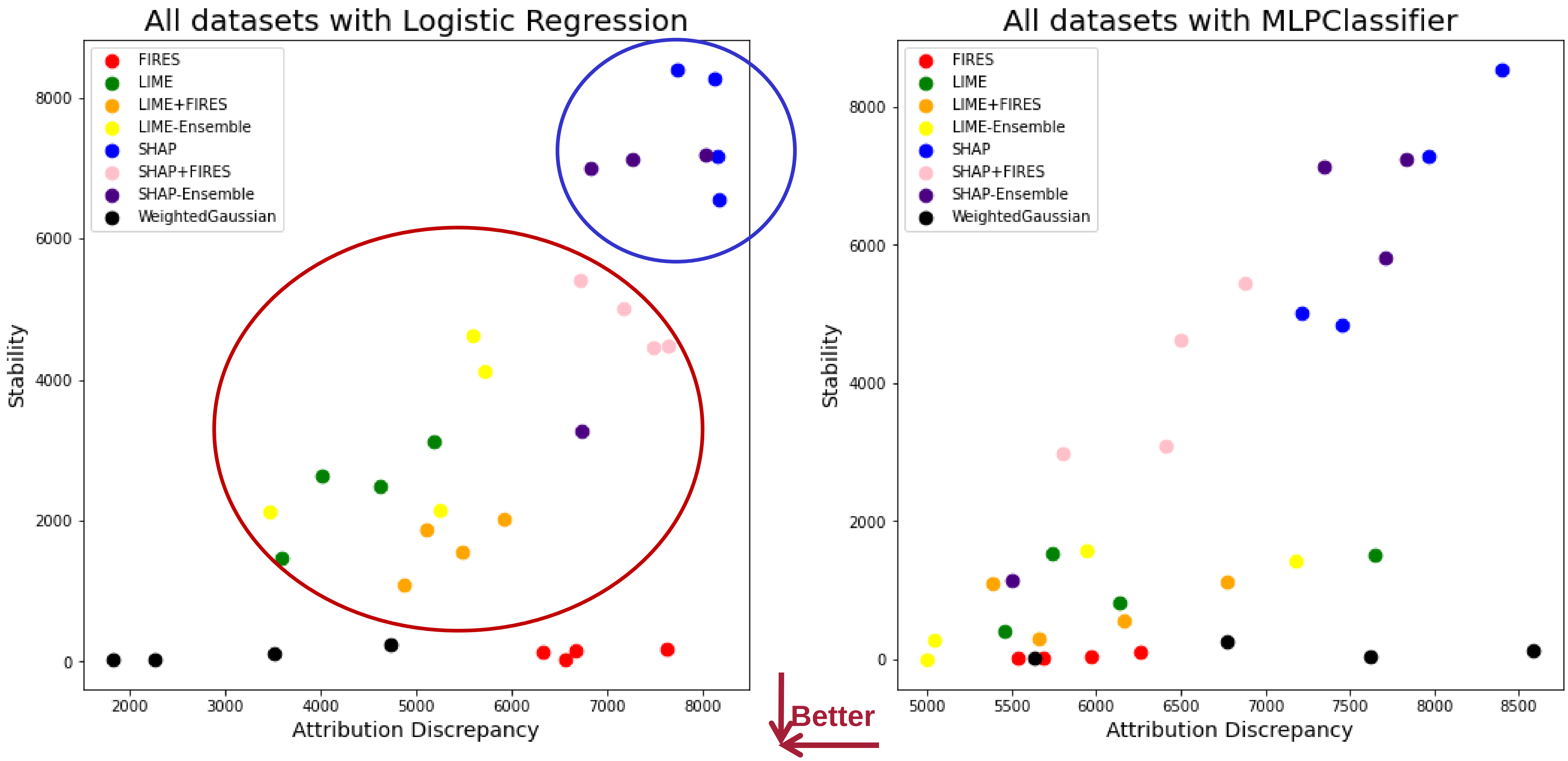

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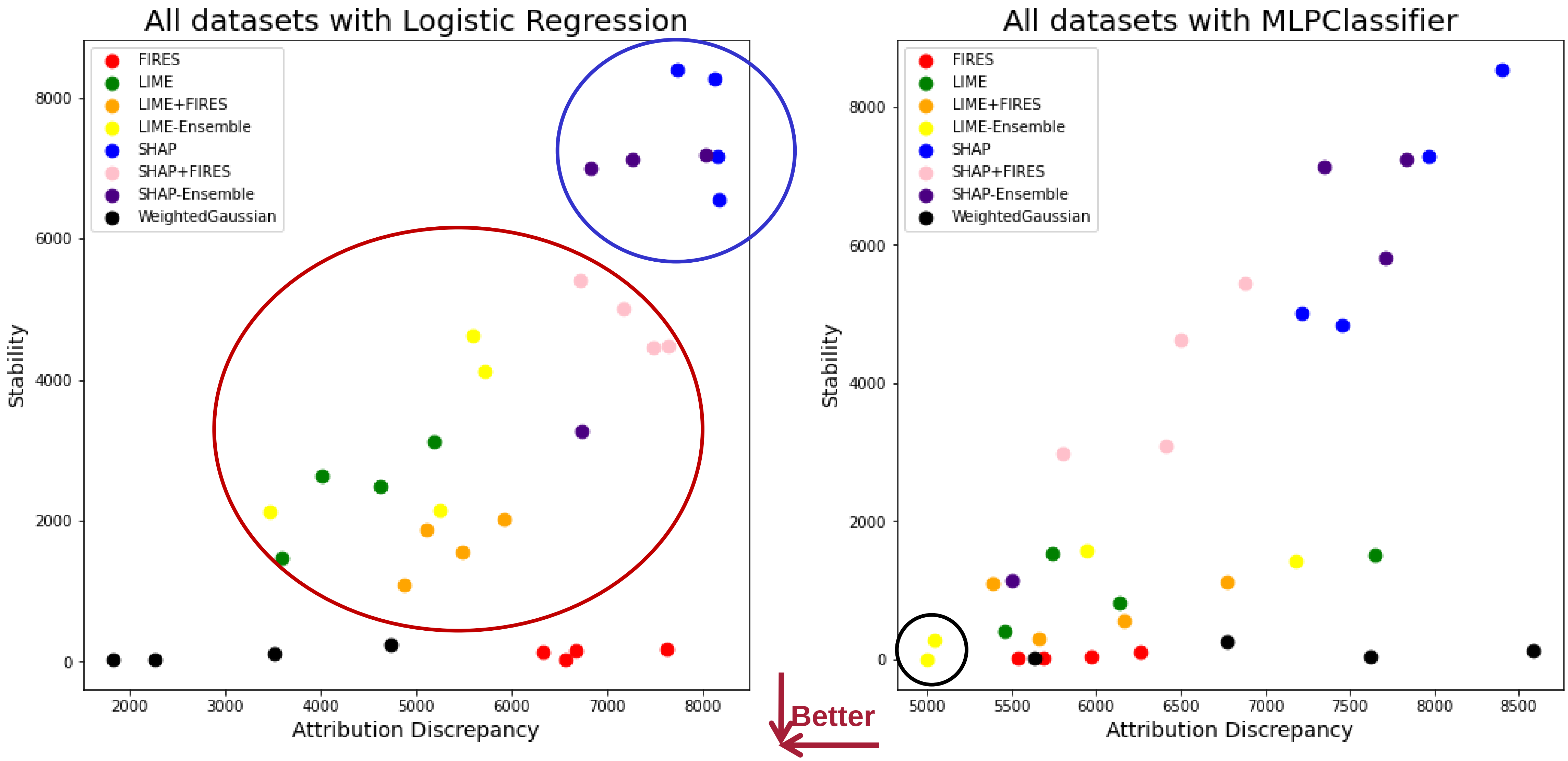

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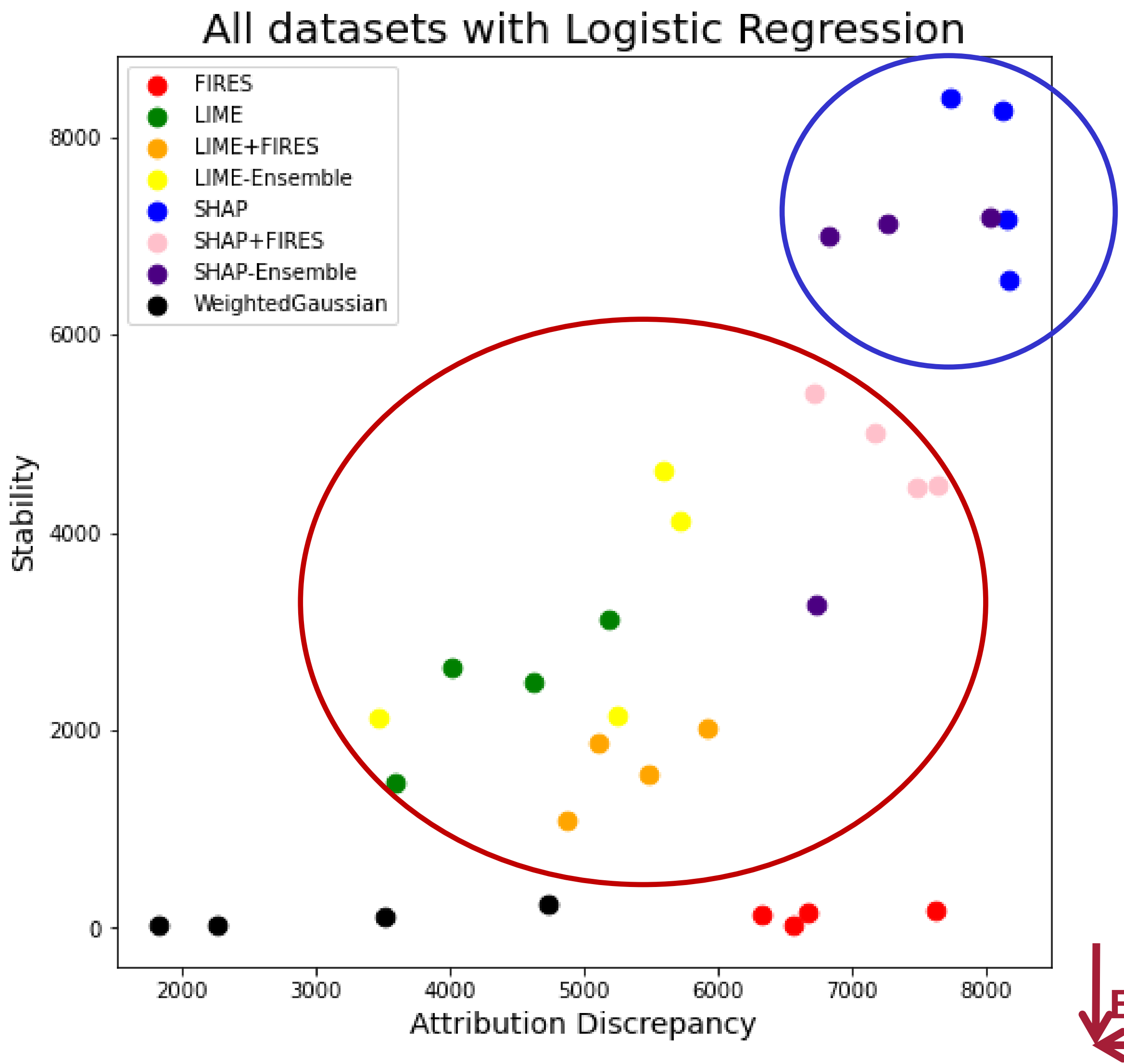

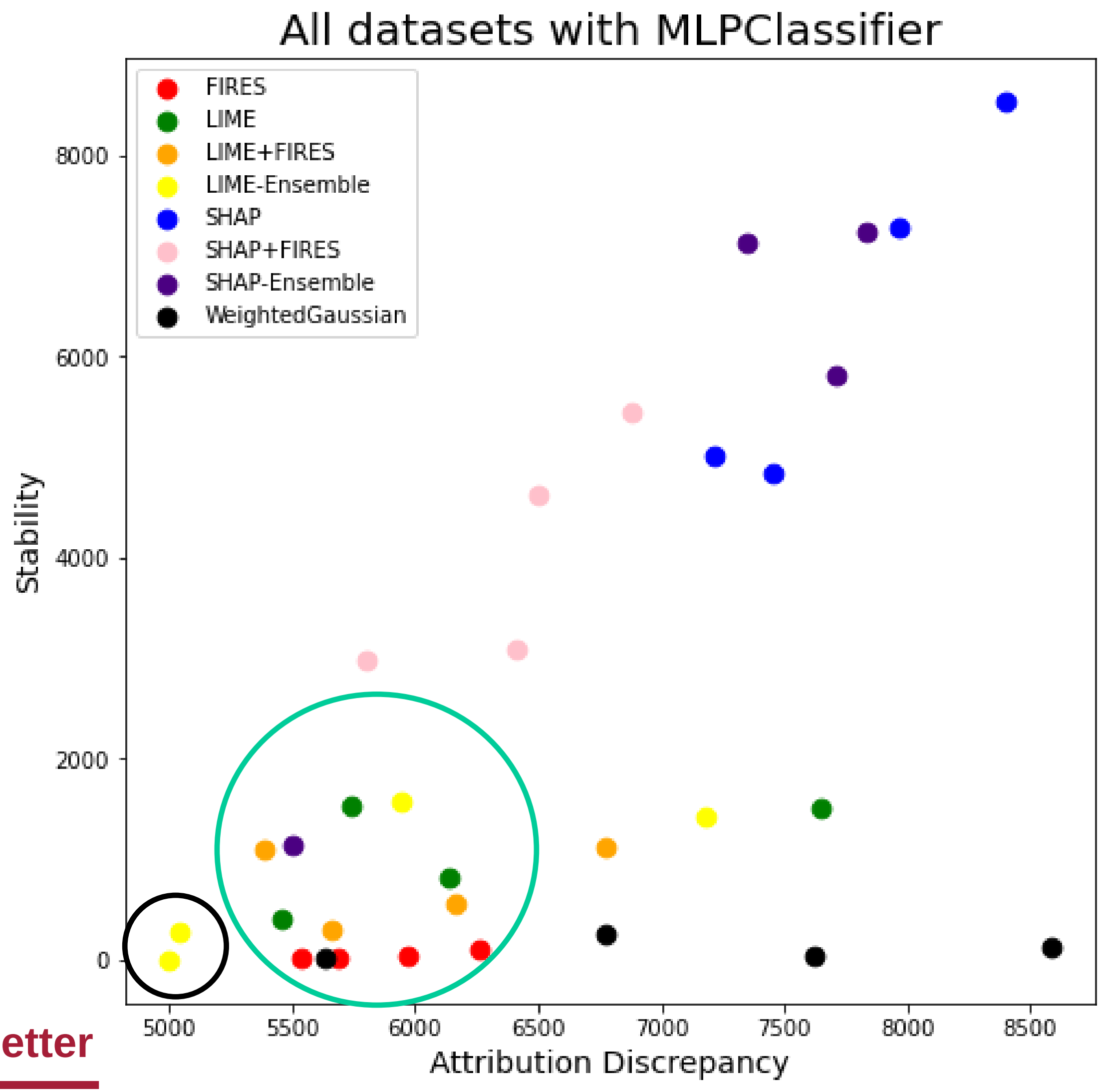

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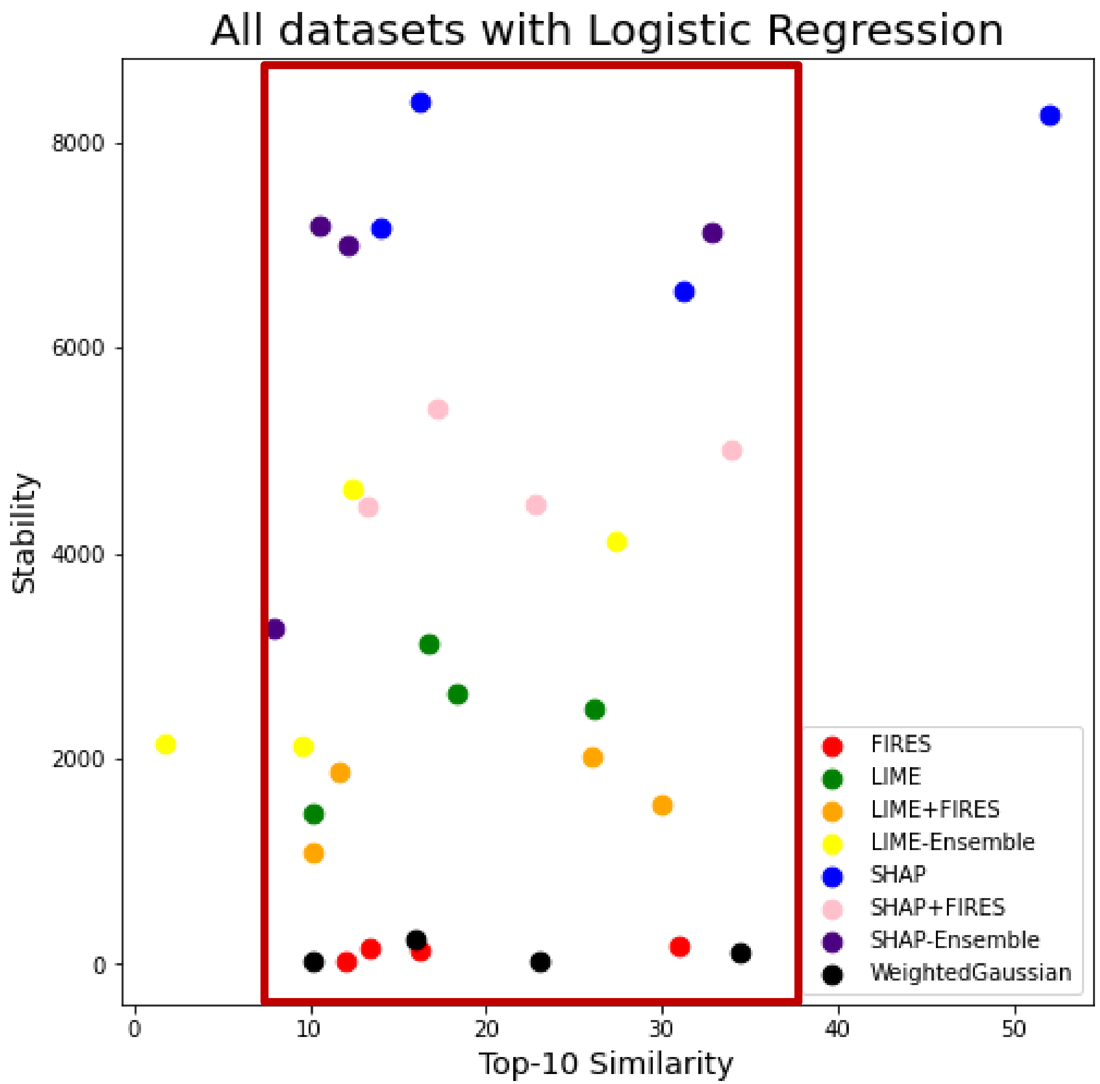

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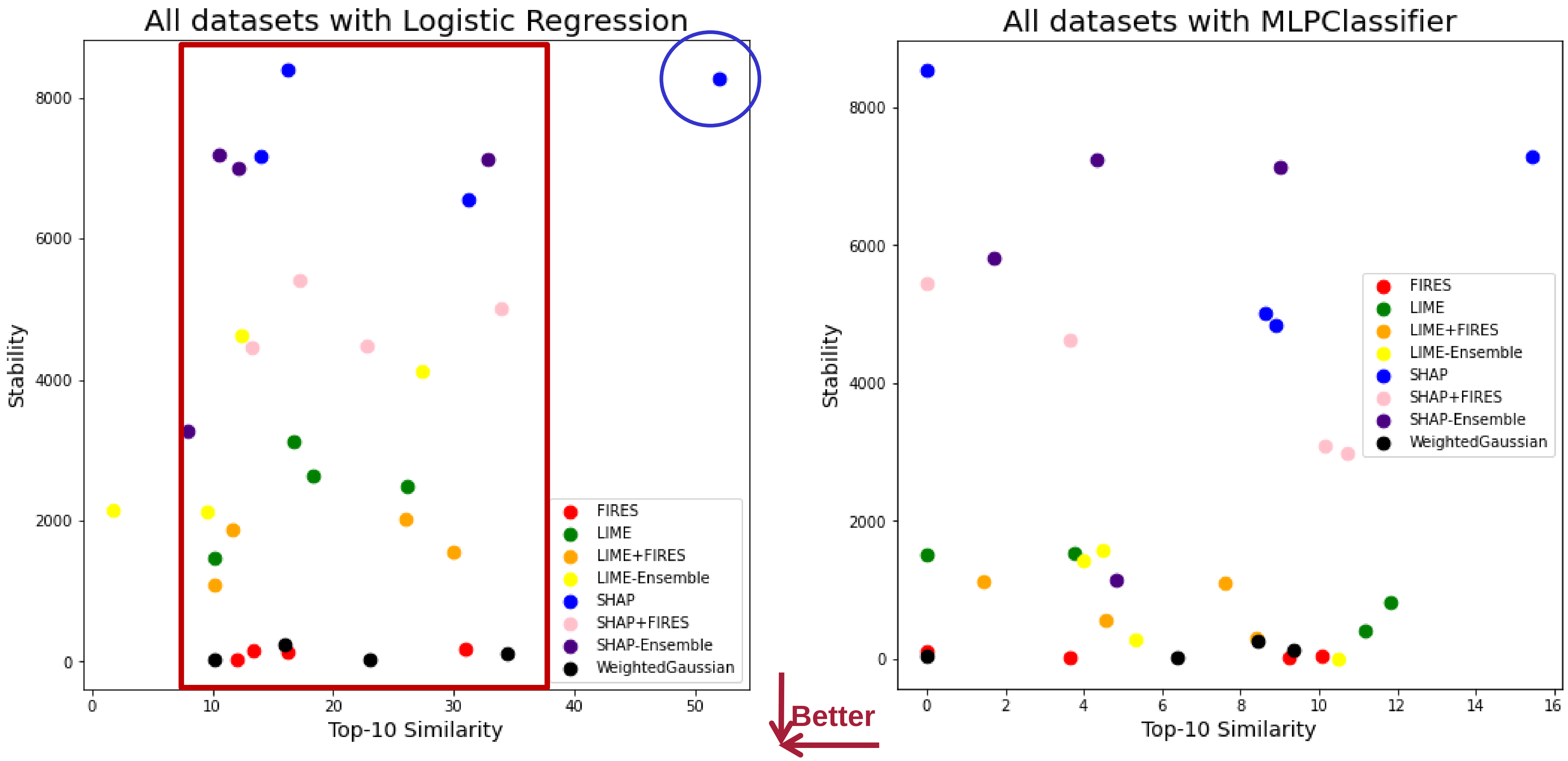

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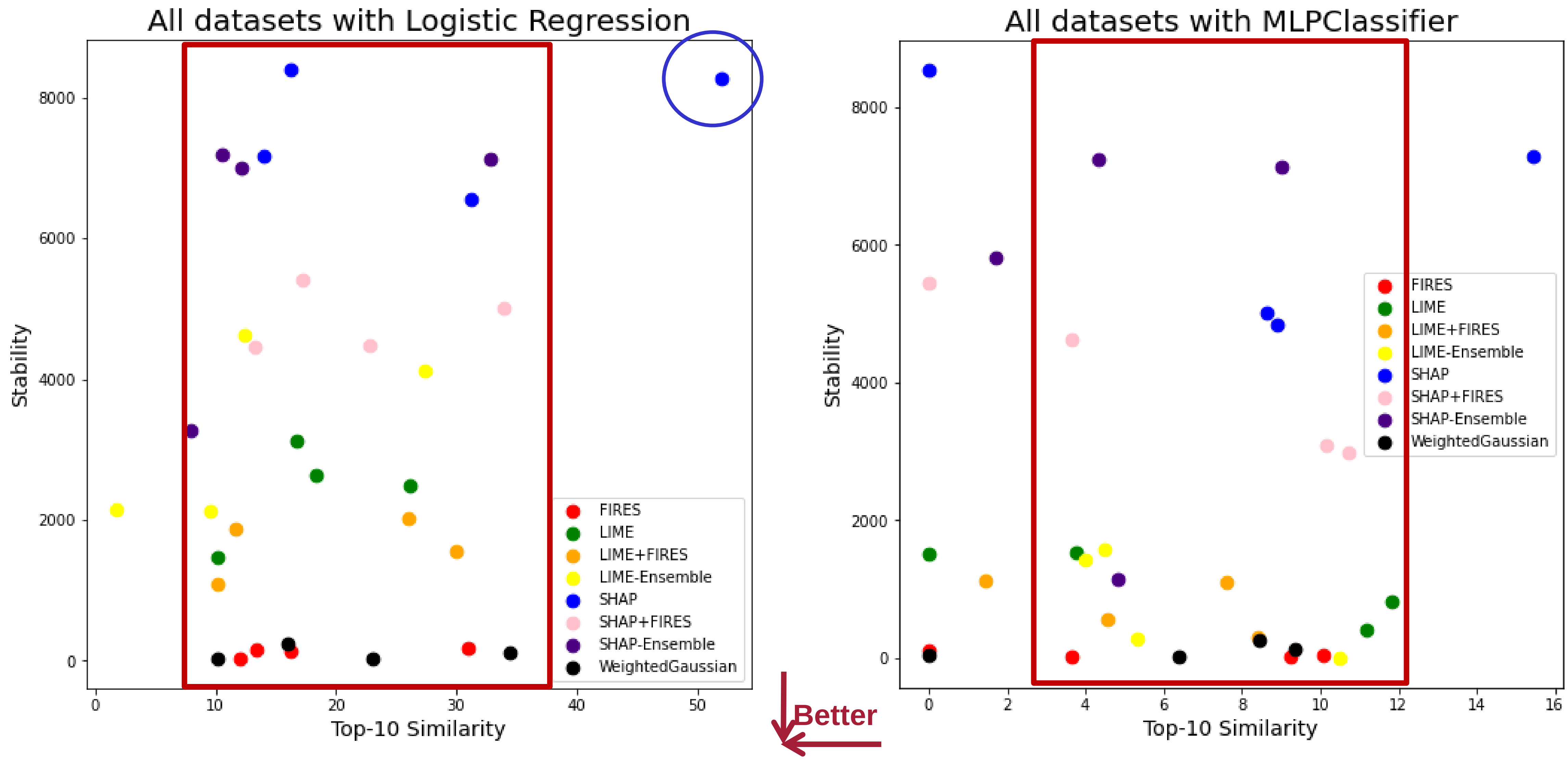

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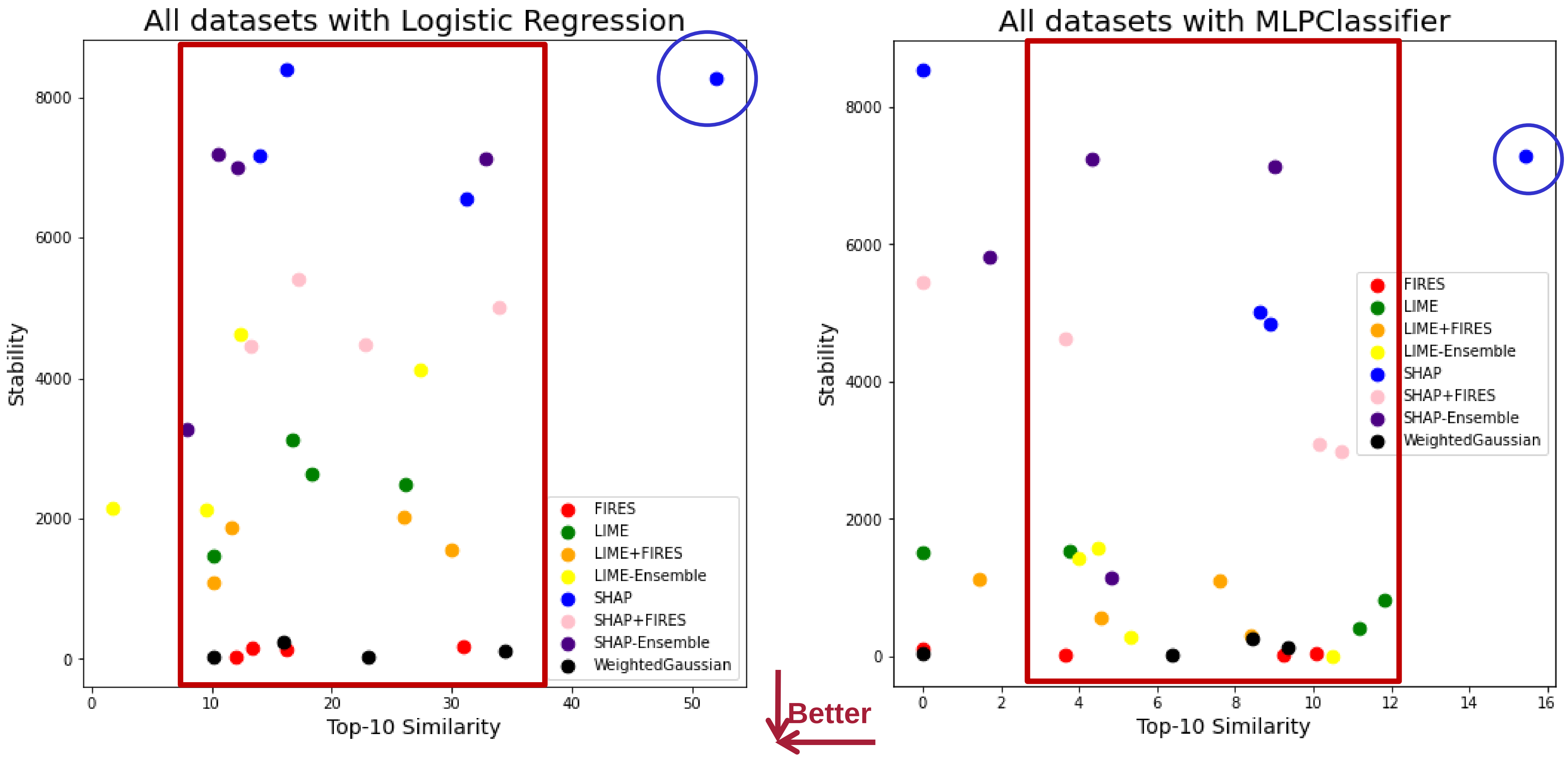

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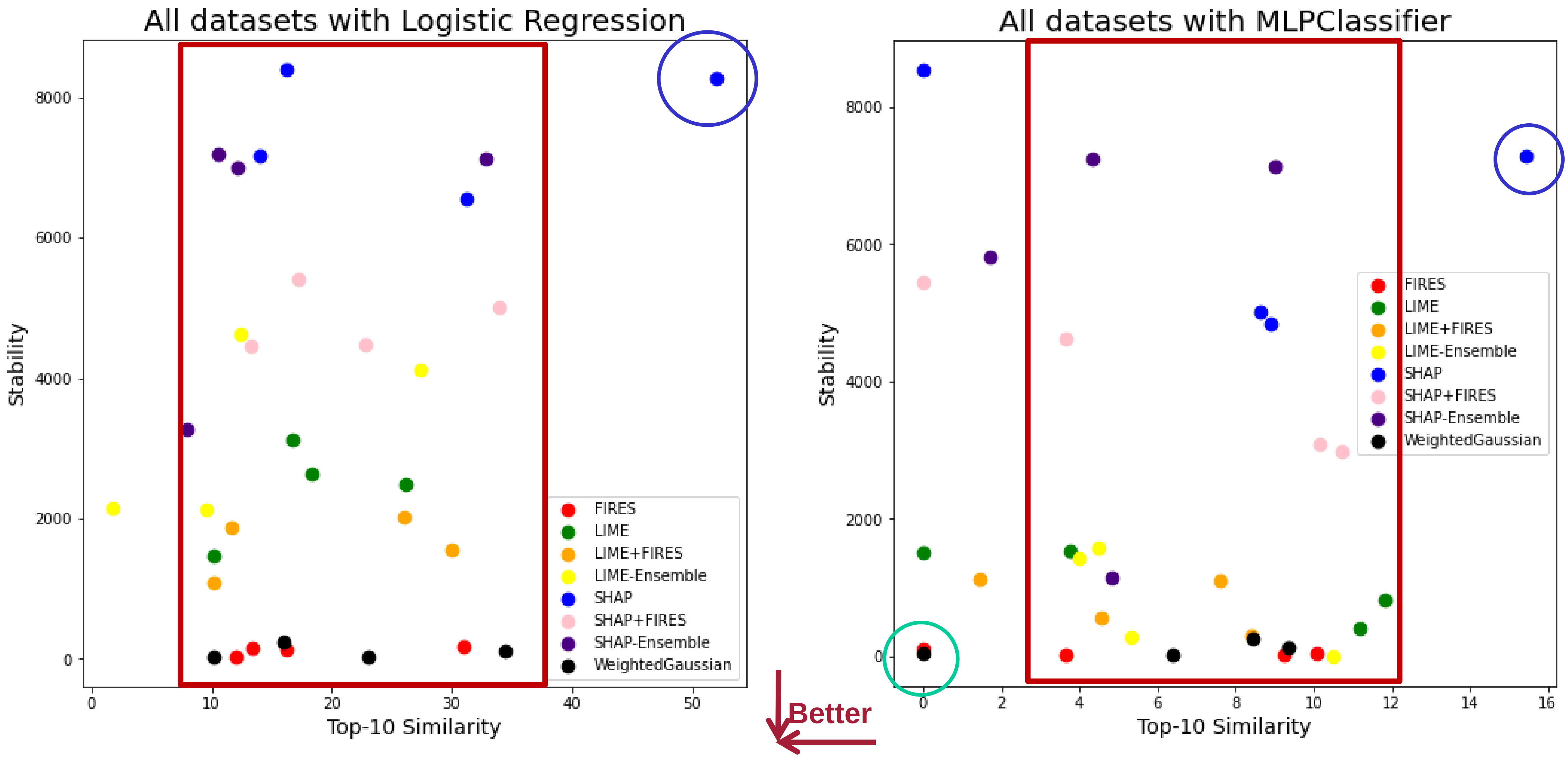

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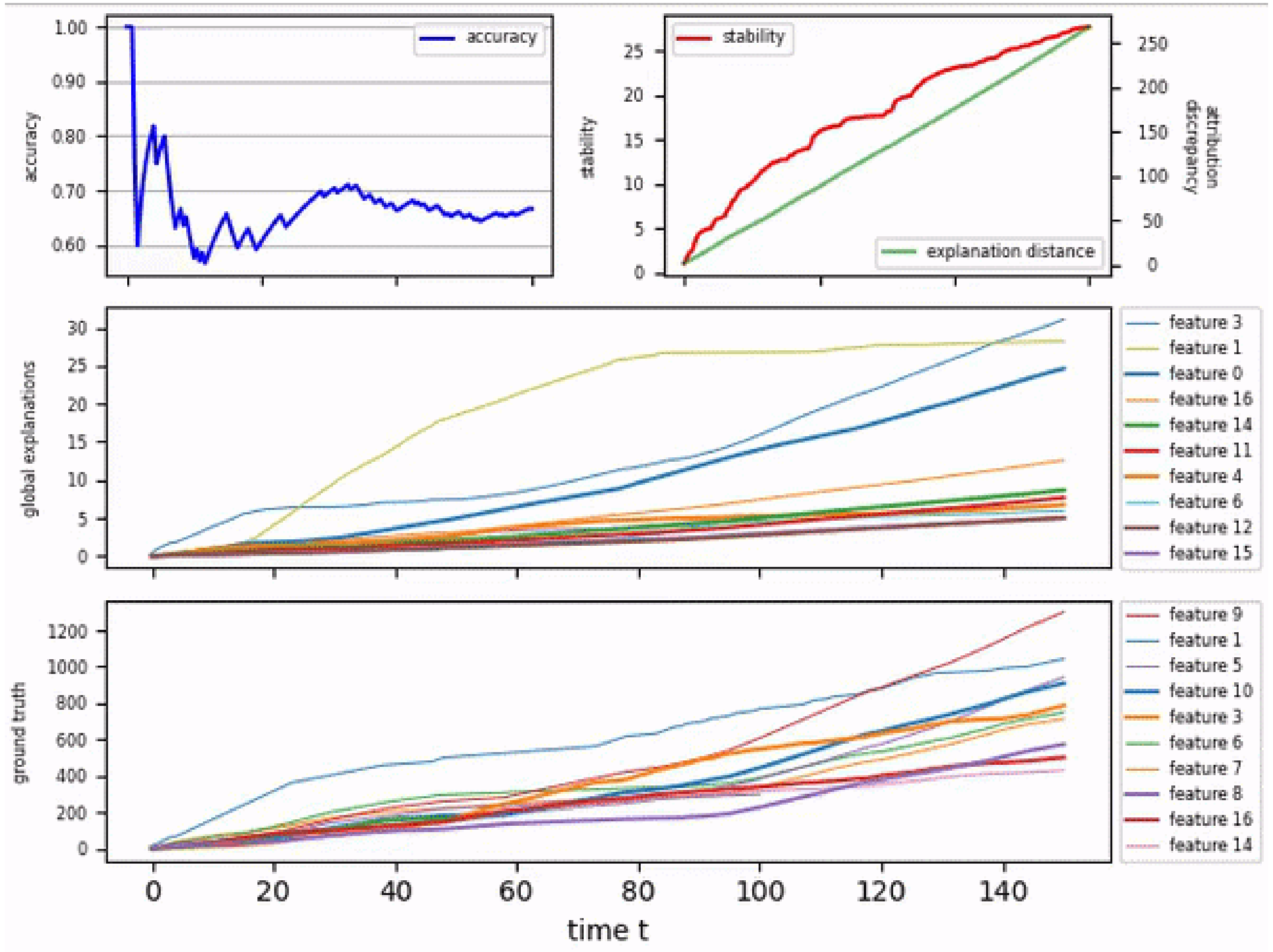
- (Time-weighted) sliding window for ranking accuracy
- Surrogate rule extraction approaches

Outlook

- (Global) explanations through visualization
- Explainer evaluation through visualization



Thank you!