Microsoft

Model Interpretability: Shedding Light on Black Box Techniques

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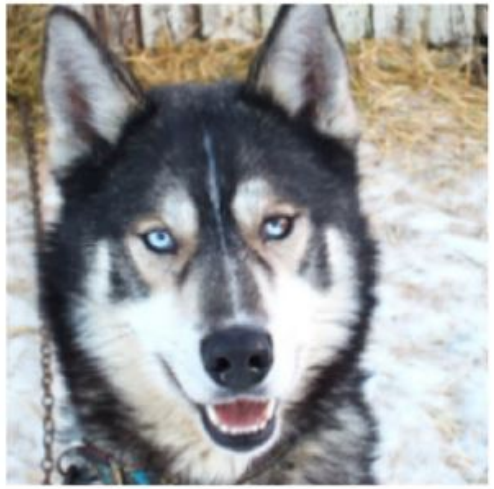
Microsoft Azure ML Platform

Interpretability for Debug

Model performance metrics aren’t enough!



(a) Husky classified as wolf

(b) Explanation

SIGKDD’16 (RSG16)

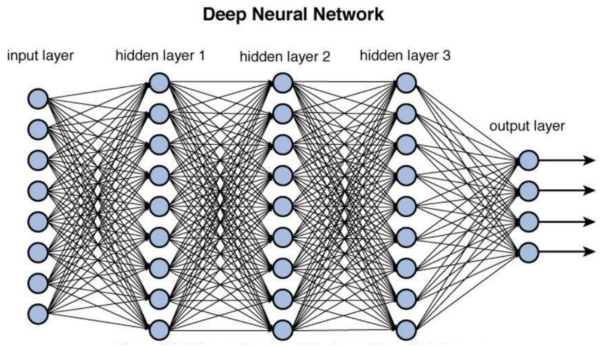
We just trained a perfect snow detector!!!

Interpretability for Regulation

The recent General Data Protection Regulation (GDPR) requirements state a right to explanation for any algorithm whose decision impacts a person's legal status:

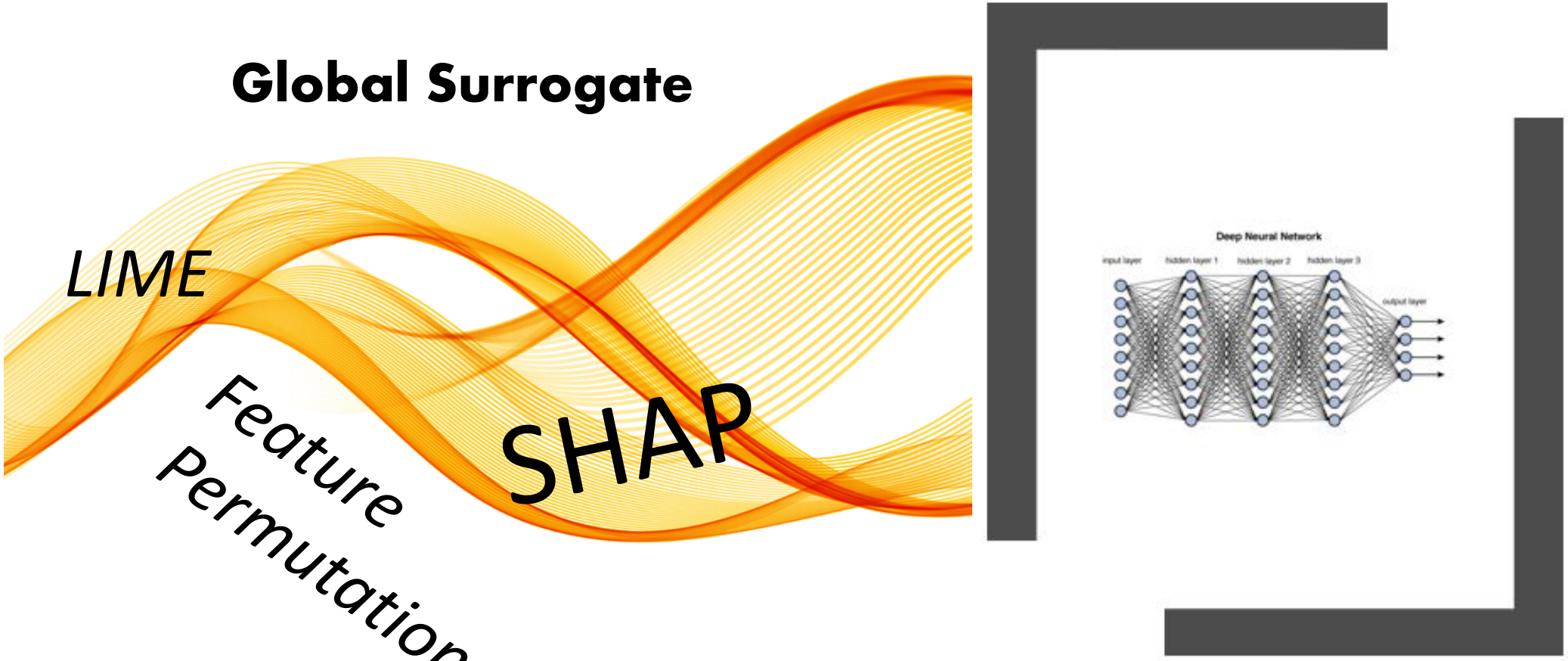
- ✓ Identifying the factors that went into a decision
- ✓ Knowing how varying a factor impacts a decision
- ✓ Comparing similar instances with different outcomes

Black Box Techniques

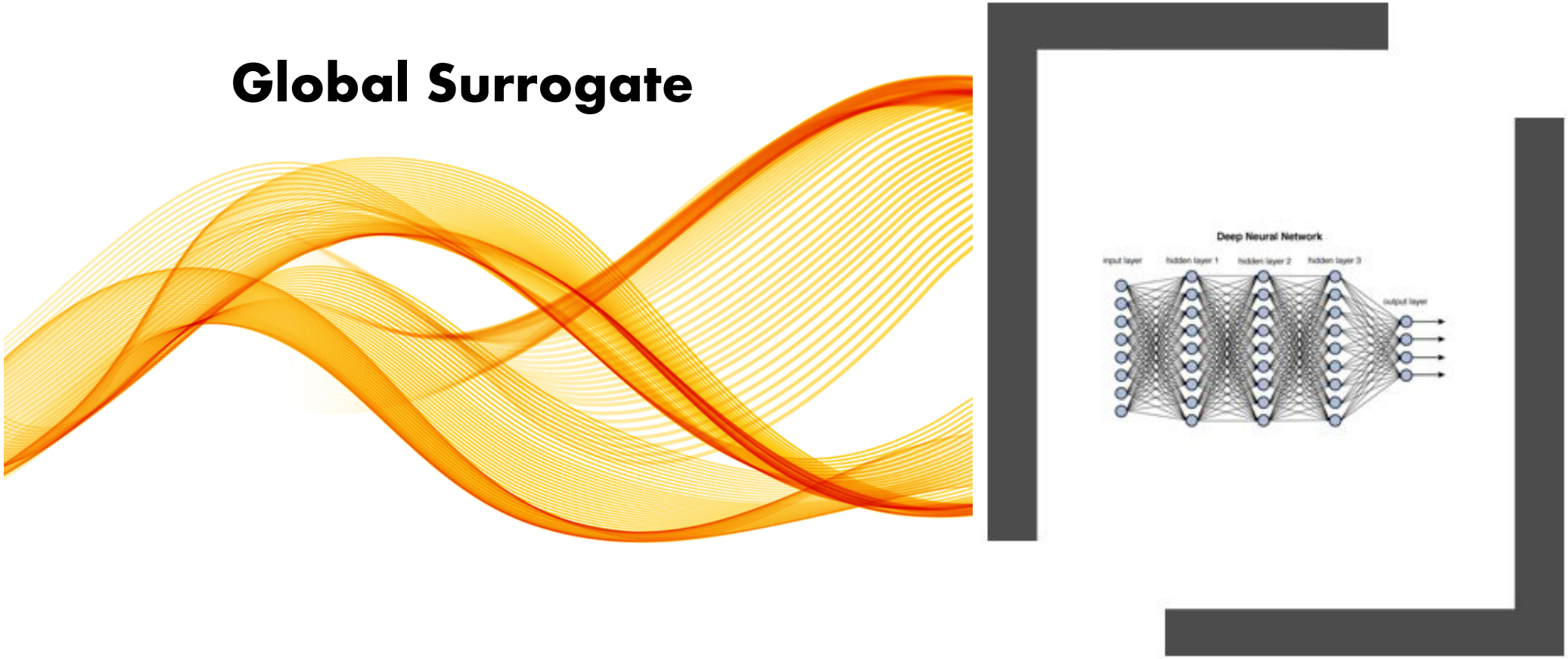


- Increased computational power allows more complex models
- Accuracy goes up and Interpretability goes down dramatically

Shedding Light on Black Box Techniques



Global Surrogate



Global Surrogate Models

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	4.98
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	9.14
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.03
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394.63	2.94
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396.90	5.33

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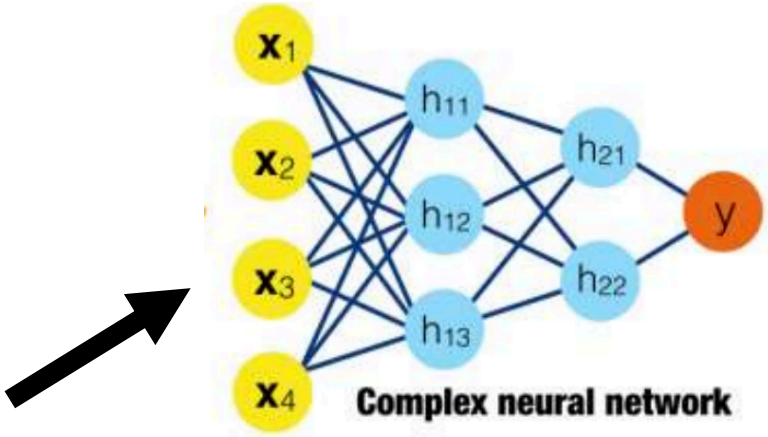

Price
24.0
21.6
34.7
33.4
36.2

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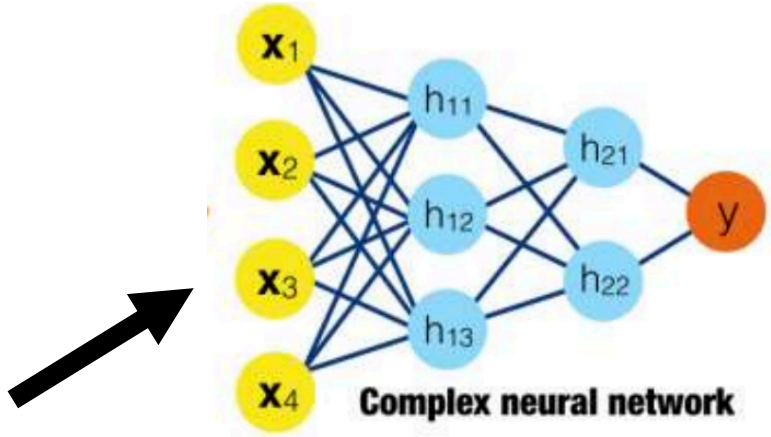

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24.0
21.6
34.7
33.4
36.2

Predictions of
the black-box model

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	Price
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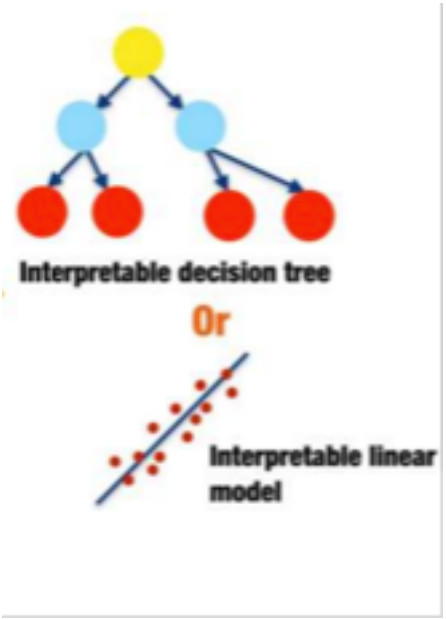
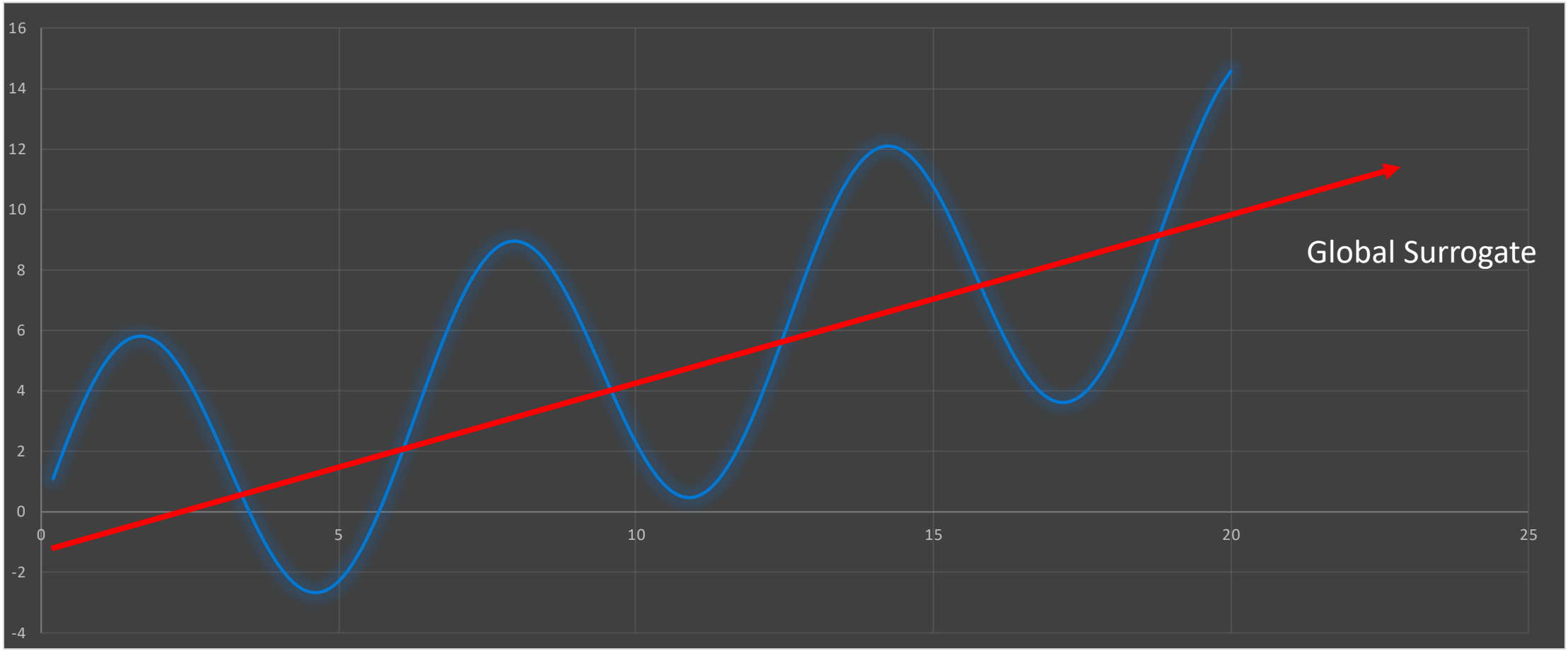
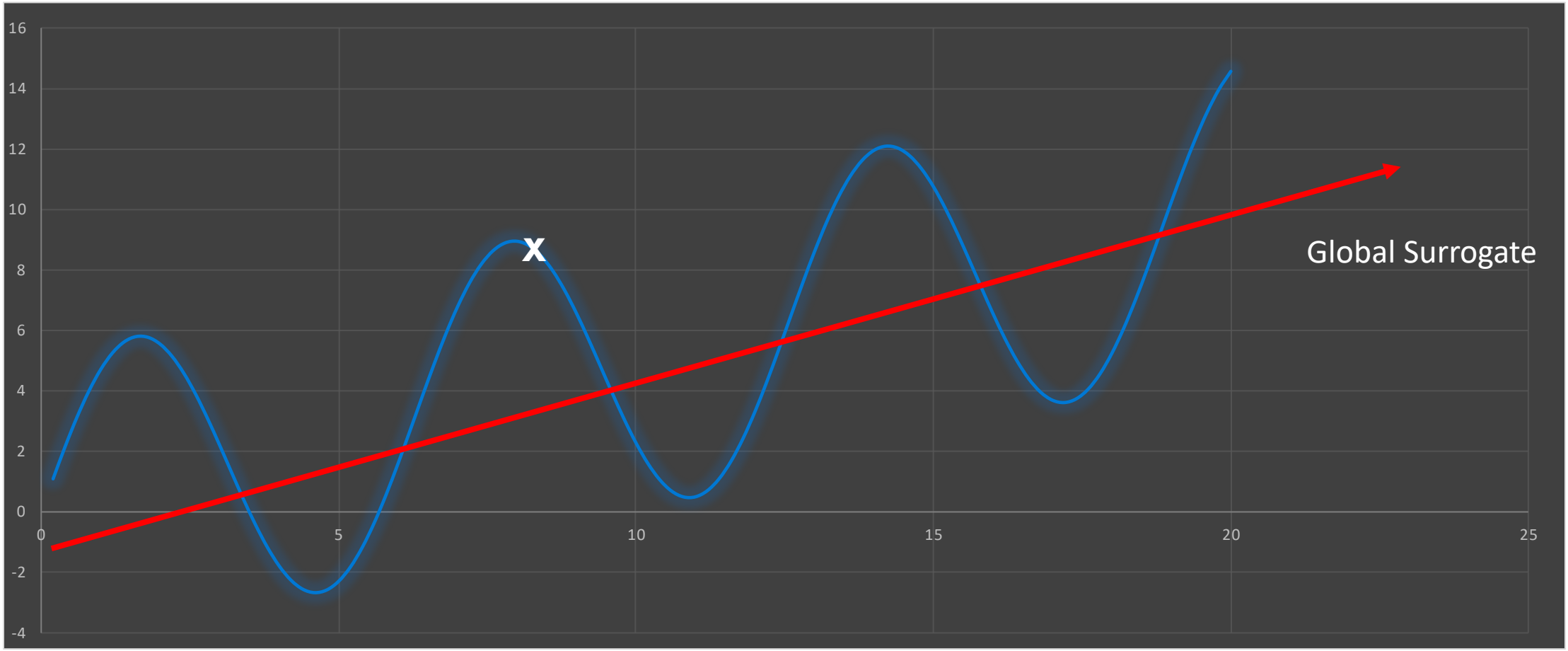


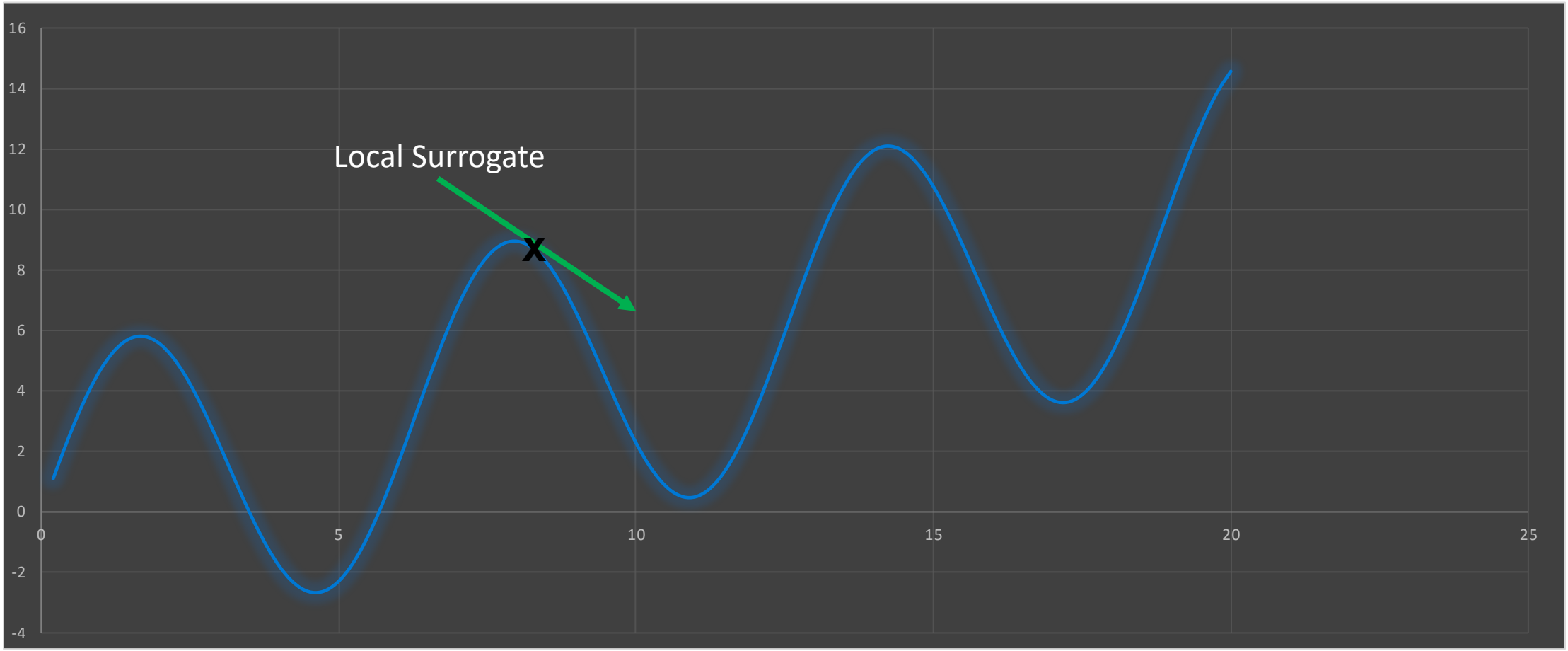
Global Surrogate Models

- Flexibility
- Fidelity measure (e.g., R-squared)
- Easy to explain to non-technical stakeholders

- You draw conclusions about the model and not about the data
- No clear cut-off for R-squared
- The interpretable surrogate model comes with all its +s and –s.

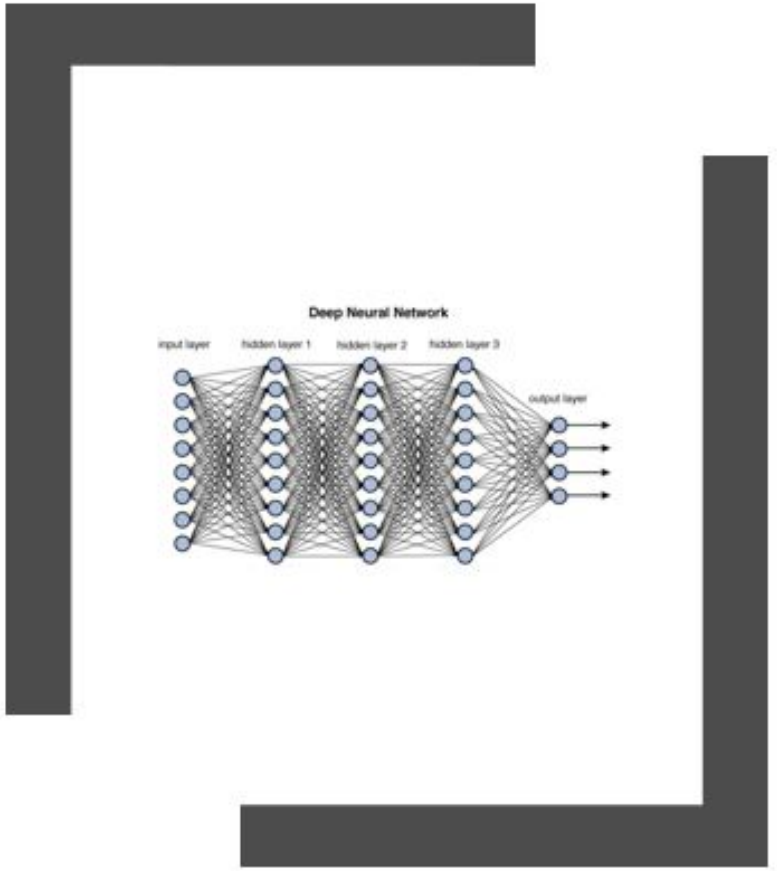

16
14
12
10
8
6
4
2
0
-2
-4
0
5
10
15
20
25
Global Surrogate


16
14
12
10
8
6
4
2
0
-2
-4
0
5
10
15
20
25
X
Global Surrogate


Local Surrogate
X
16
14
12
10
8
6
4
2
0
-2
-4
0
5
10
15
20
25

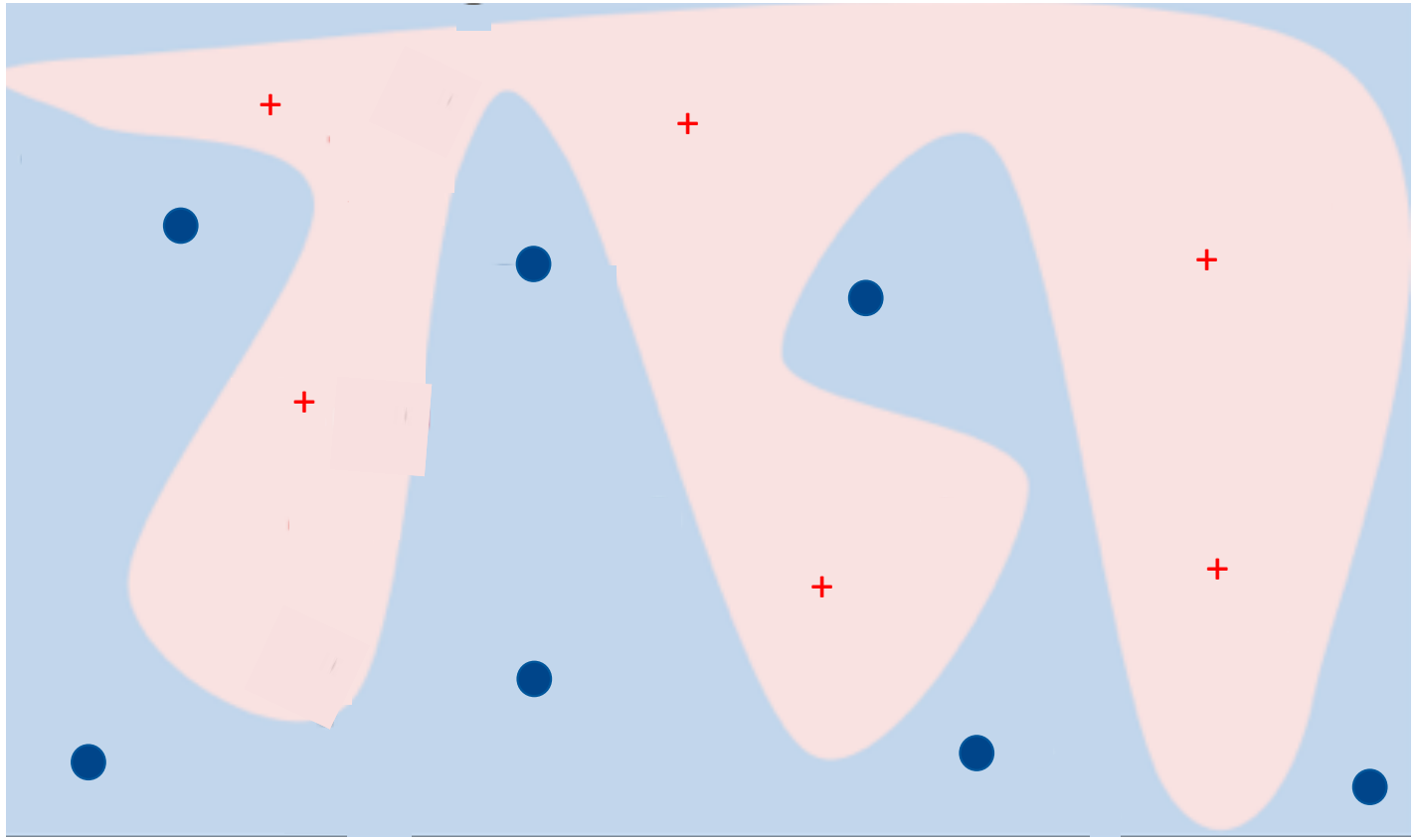
Local Interpretable Model-Agnostic Explanations

LIME

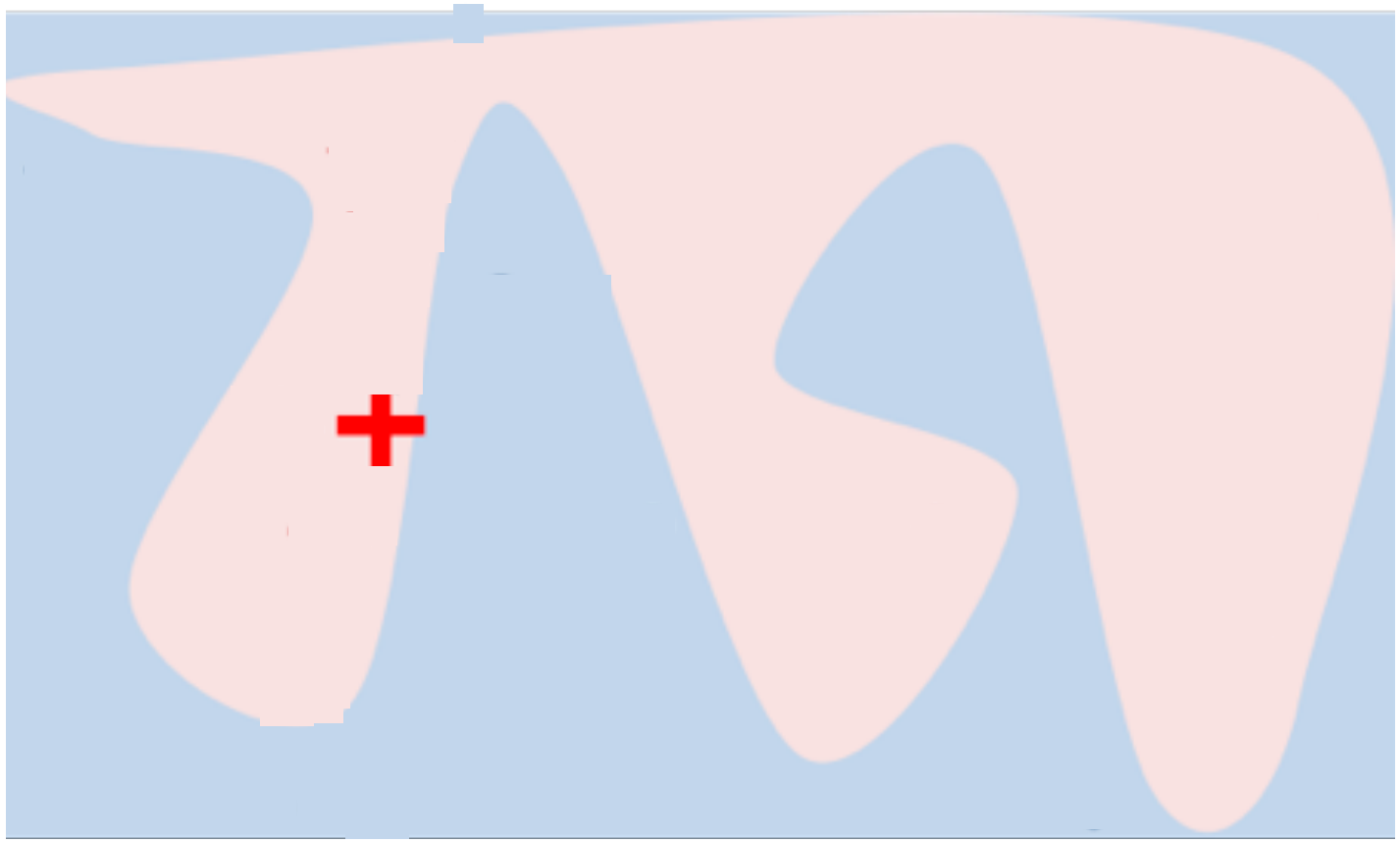


Local Interpretable Model-agnostic Explanations (LIME)

- LIME focuses on training local surrogate models to explain individual predictions.

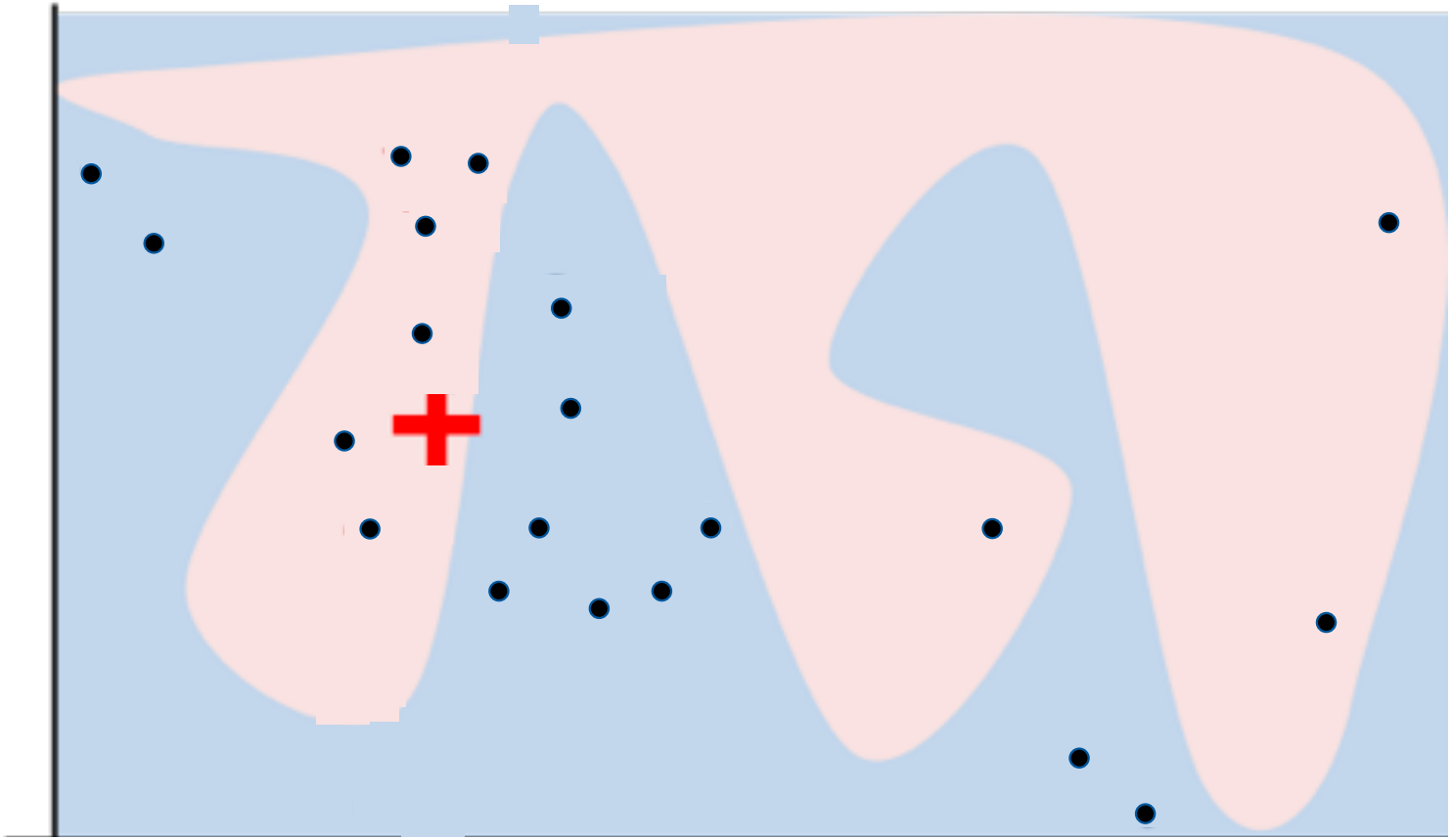


Local Interpretable Model-agnostic Explanations (LIME)



Local Interpretable Model-agnostic Explanations (LIME)

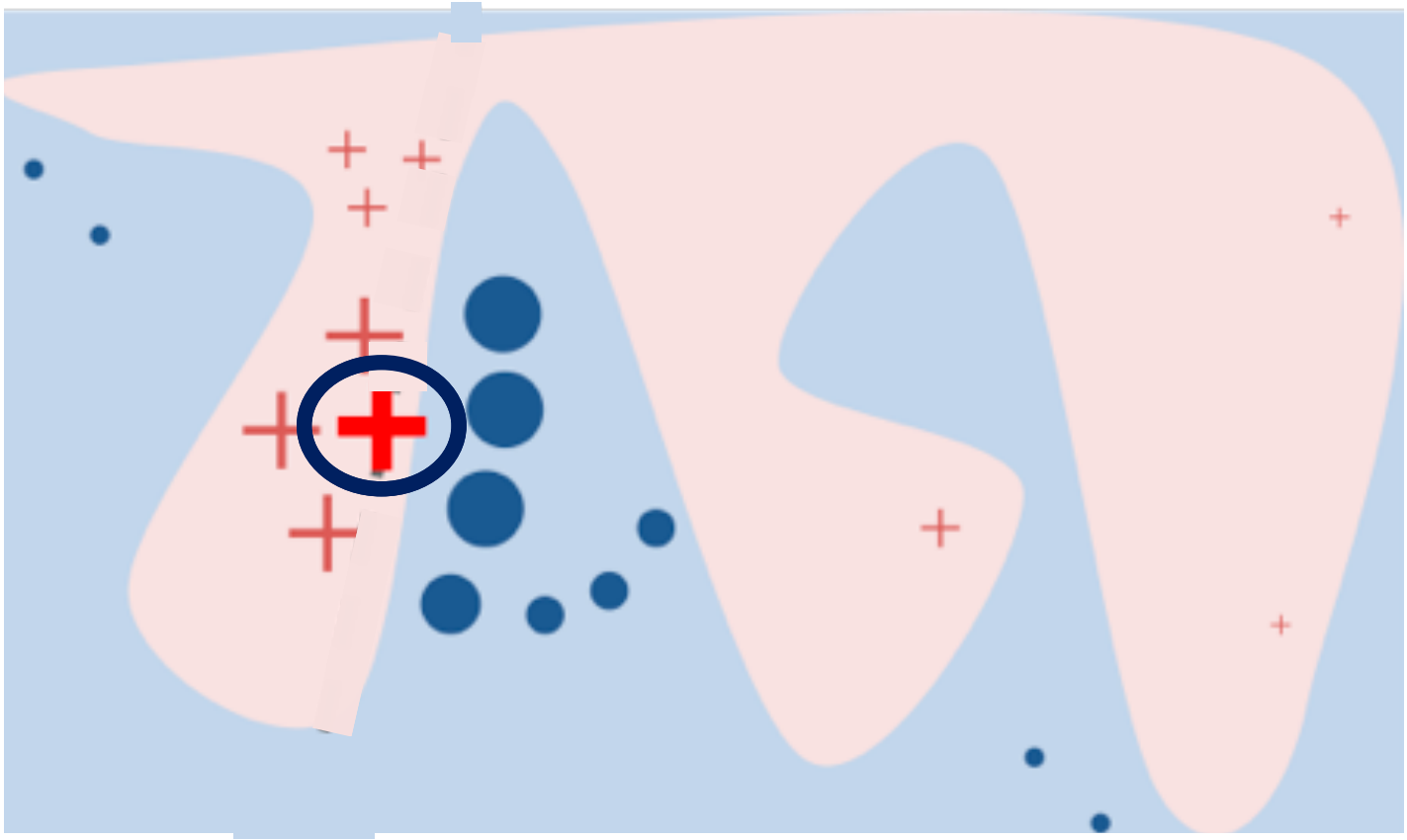
- Permute data (take the point of interest and create fake data around it)



Local Interpretable Model-agnostic Explanations (LIME)

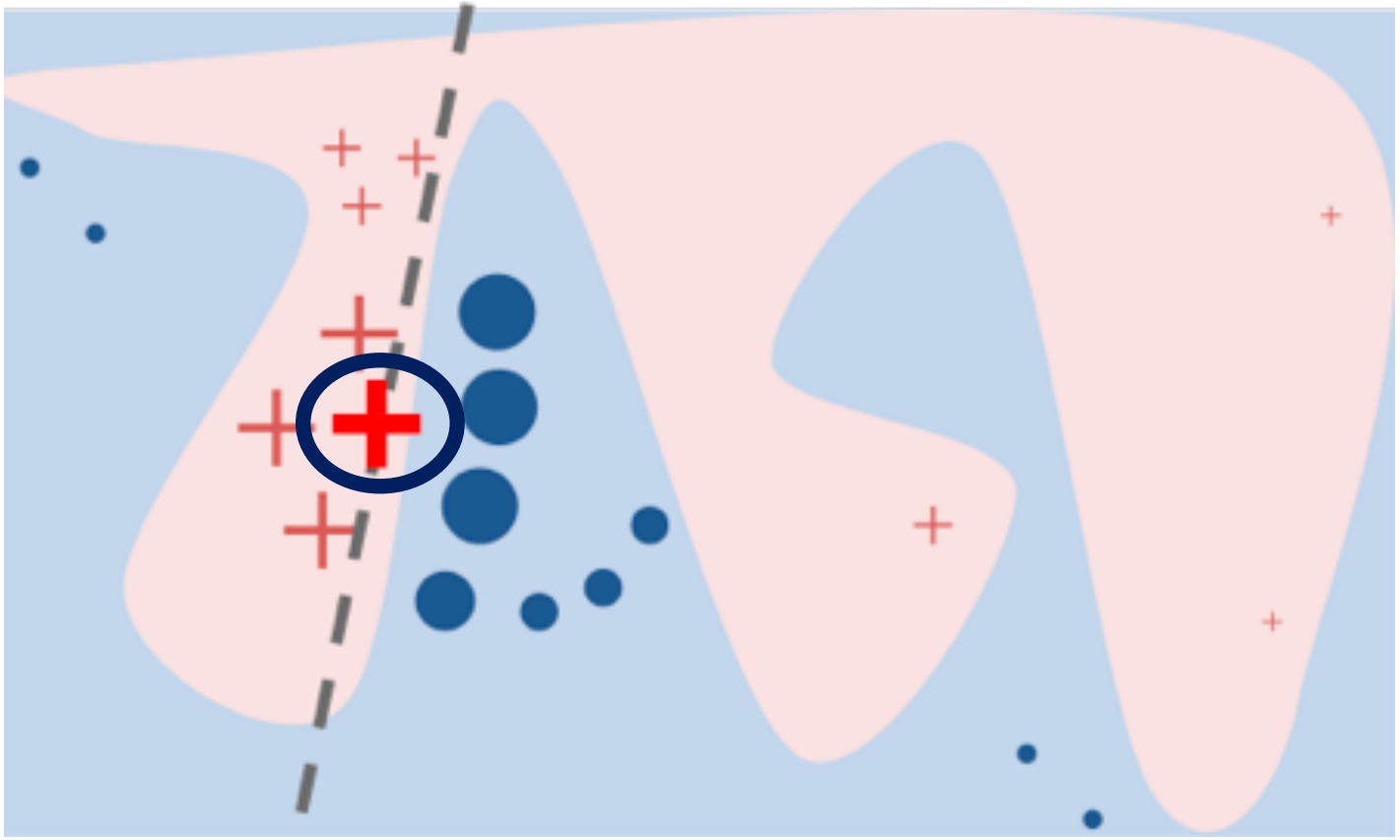
- Take the black box model and make predictions on this new dataset (shown by signs)

- Calculate distance between fake and original data (shown by size)



Local Interpretable Model-agnostic Explanations (LIME)

- Fit an interpretable model on the permuted data with similarity scores

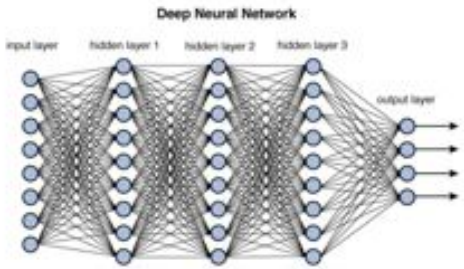


Local Interpretable Model-agnostic Explanations

- Flexibility
- Fidelity measure
- Works for tabular data, text, and image

- Perturbation Stage: **unlikely data points** which can then be used to learn local explanation models.
- **Instability of the explanations**: if you repeat the sampling process, then the explanations that come out can be different.

SHAP


Deep Neural Network
input layer
hidden layer 1
hidden layer 2
hidden layer 3
output layer

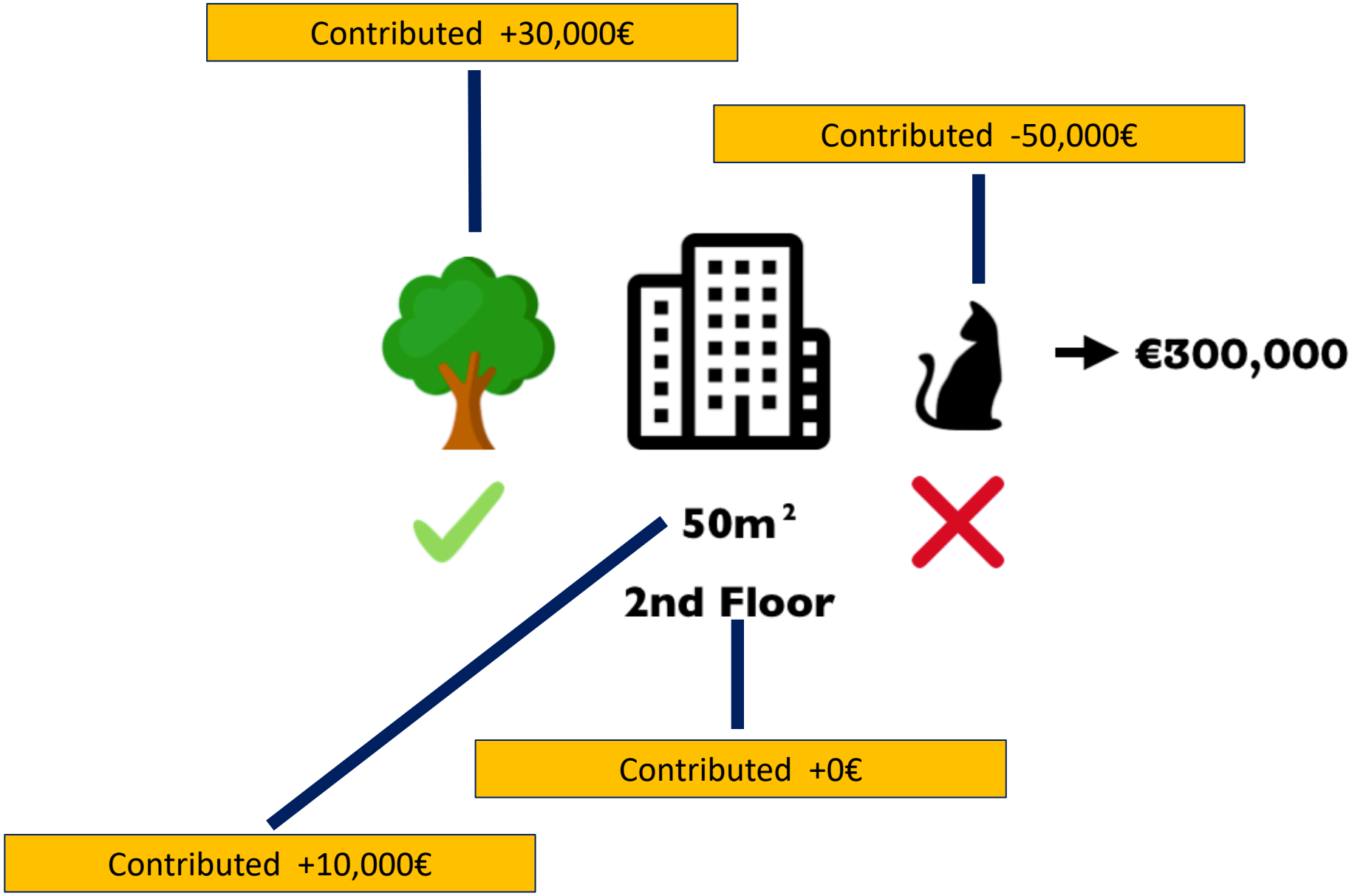
SHAP

- Not a new concept
- Concept based on game theory
- Mathematically sound
- Application in MI relatively new

SHAP

How much has each feature contributed to the prediction compared to the average prediction?

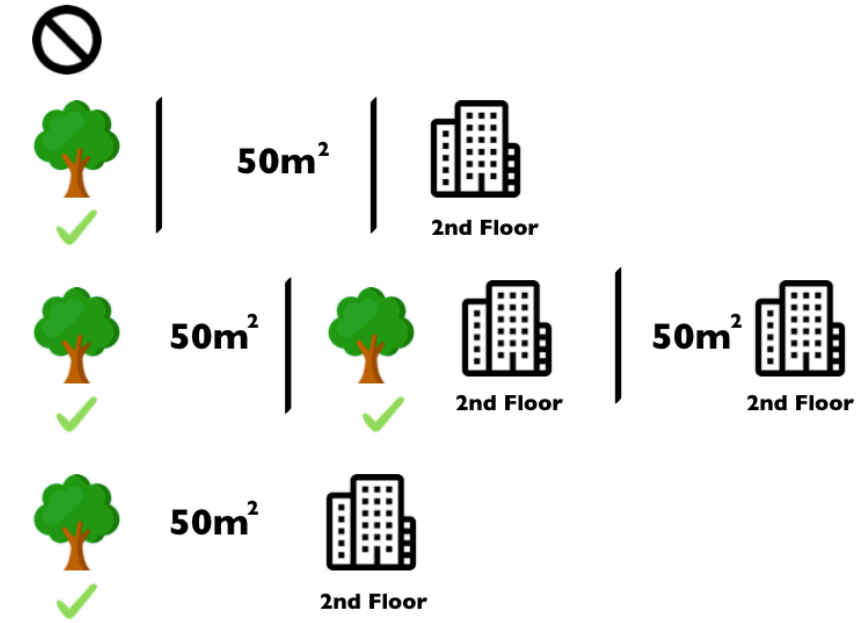
- House price prediction: 300,000€
- Average house price prediction for all apartments is 310,000€
- Delta here is -10,000€

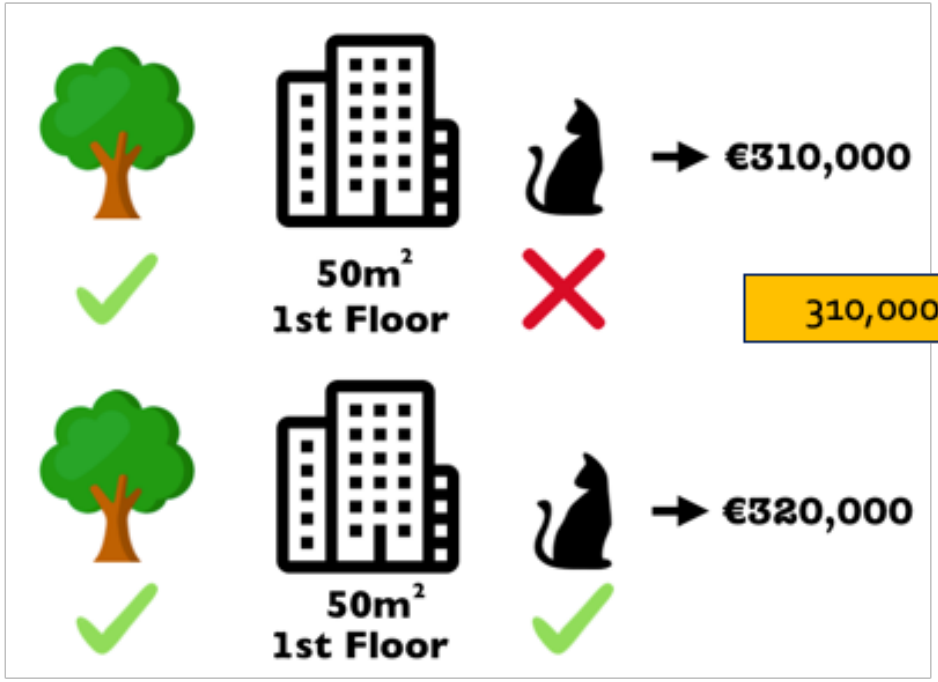

Contributed +30,000€
Contributed -50,000€
€300,000
50m²
2nd Floor
Contributed +0€
Contributed +10,000€

SHAP

How do we calculate Shapley values?

- Take your feature of interest (e.g., cats-banned) and remove it from the feature set
- Take the remaining features and generate all possible coalitions
- Add and remove your feature of interested to each of the coalitions and calculate the difference it makes





310,000 – 320,000 = -10,000€

SHAP

- Based on a solid theory and distributes the effects fairly
- **Contrastive explanations**. Instead of comparing a prediction to the average prediction of the entire dataset, you could compare it to a subset or even to a single data point.

- Computation time: 2^k possible coalitions of the feature values for k features
- **Can be misinterpreted**
- **Inclusion of unrealistic data instances** when features are correlated.

Machine Learning Interpretability