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Machine Learning

Session 24 - T

Explainable AI (XAI)

Degree in Applied Data Science

2024/2025

Explainable AI (XAI) Motivation

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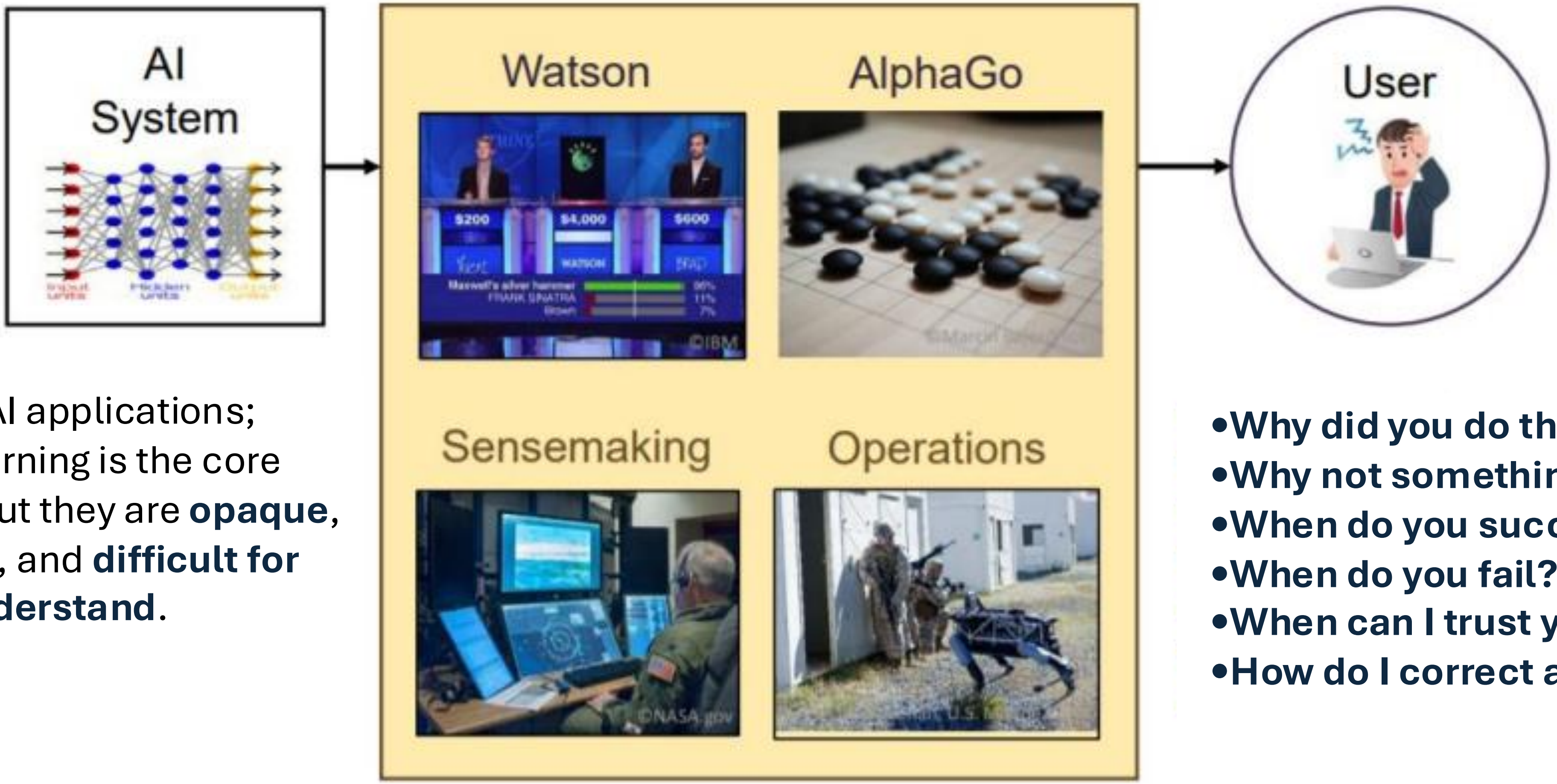
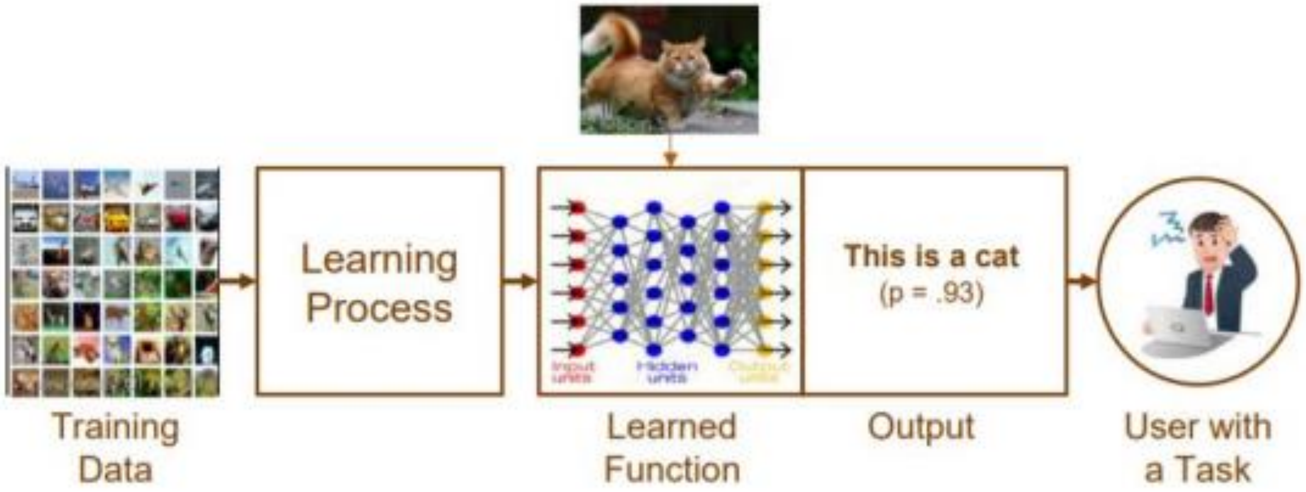


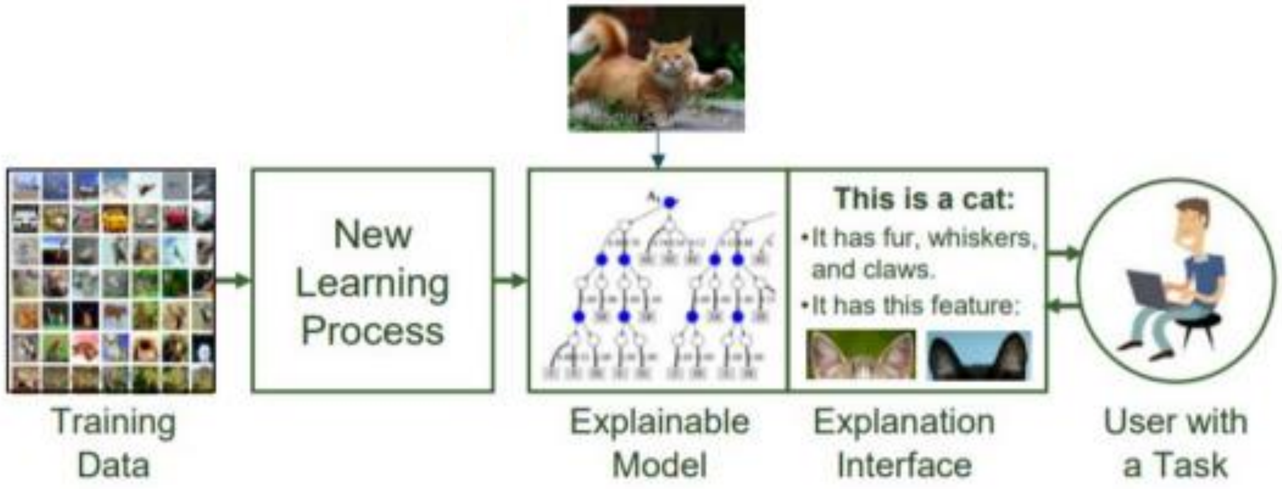
- New era of AI applications;
- Machine learning is the core technology, but they are **opaque**, **non-intuitive**, and **difficult for people to understand**.

- **Why did you do that?**
- **Why not something else?**
- **When do you succeed?**
- **When do you fail?**
- **When can I trust you?**
- **How do I correct an error?**

XAI Objective



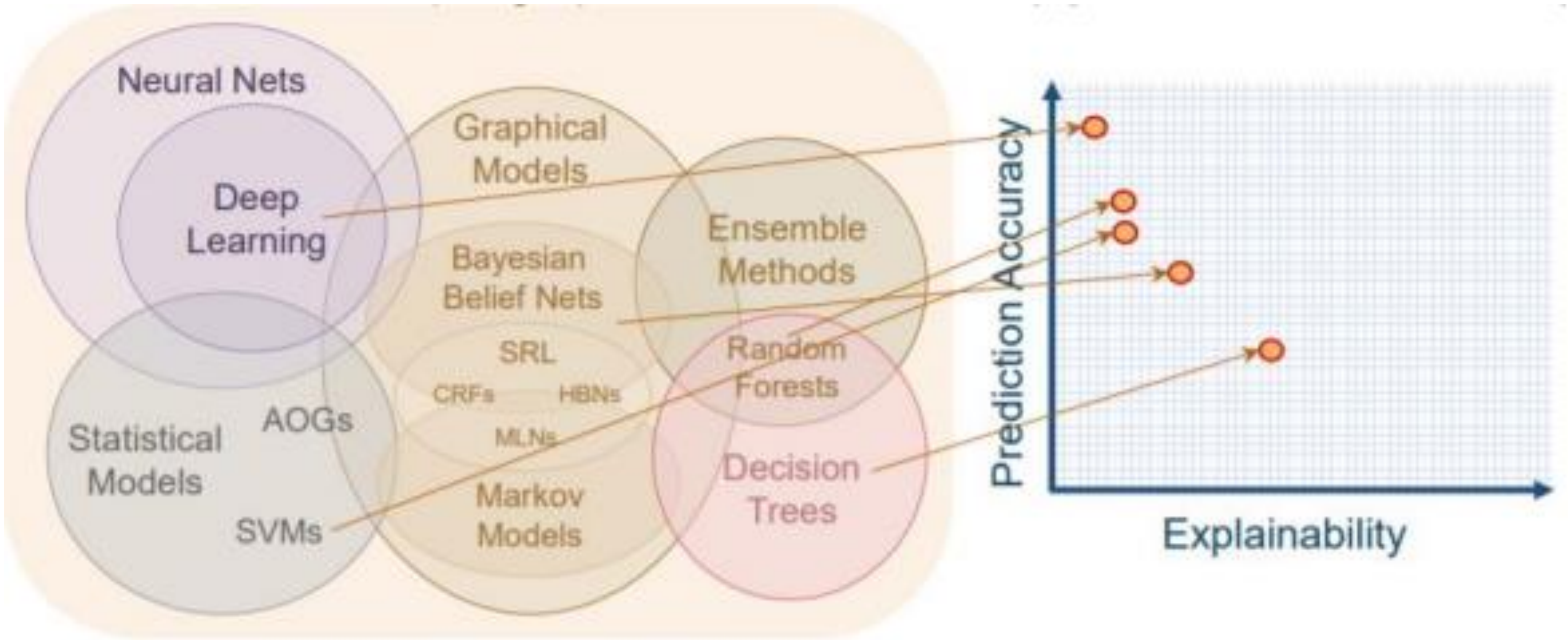
- Why did you do that?
- Why not something else?
- When do you succeed?
- When do you fail?
- When can I trust you?
- How do I correct an error?



- I understand why.
- I understand why not.
- I know when you will succeed.
- I know when you will fail.
- I know when to trust you.
- I know why you made a mistake.

Performance Vs Explainability

- **Challenge:** Develop machine learning techniques that produce more **explainable models** while maintaining a **high level of performance**.



What is a good explanation?

- Explanation not only answers **"why this"**, but also **"why this instead of that"**!

- **Q:** “Why did Jane get the promotion (while Bob didn’t)?”
- **A1:** “Jane completed her project successfully.”
  - But Bob also completed his project successfully!
    - That doesn’t explain why she got the promotion!

- **A2:** “Jane completed her project successfully and consistently demonstrated leadership skills.”
  - Bob struggled with leadership, so this explains why Jane got the promotion and Bob did not.

What is a good explanation?

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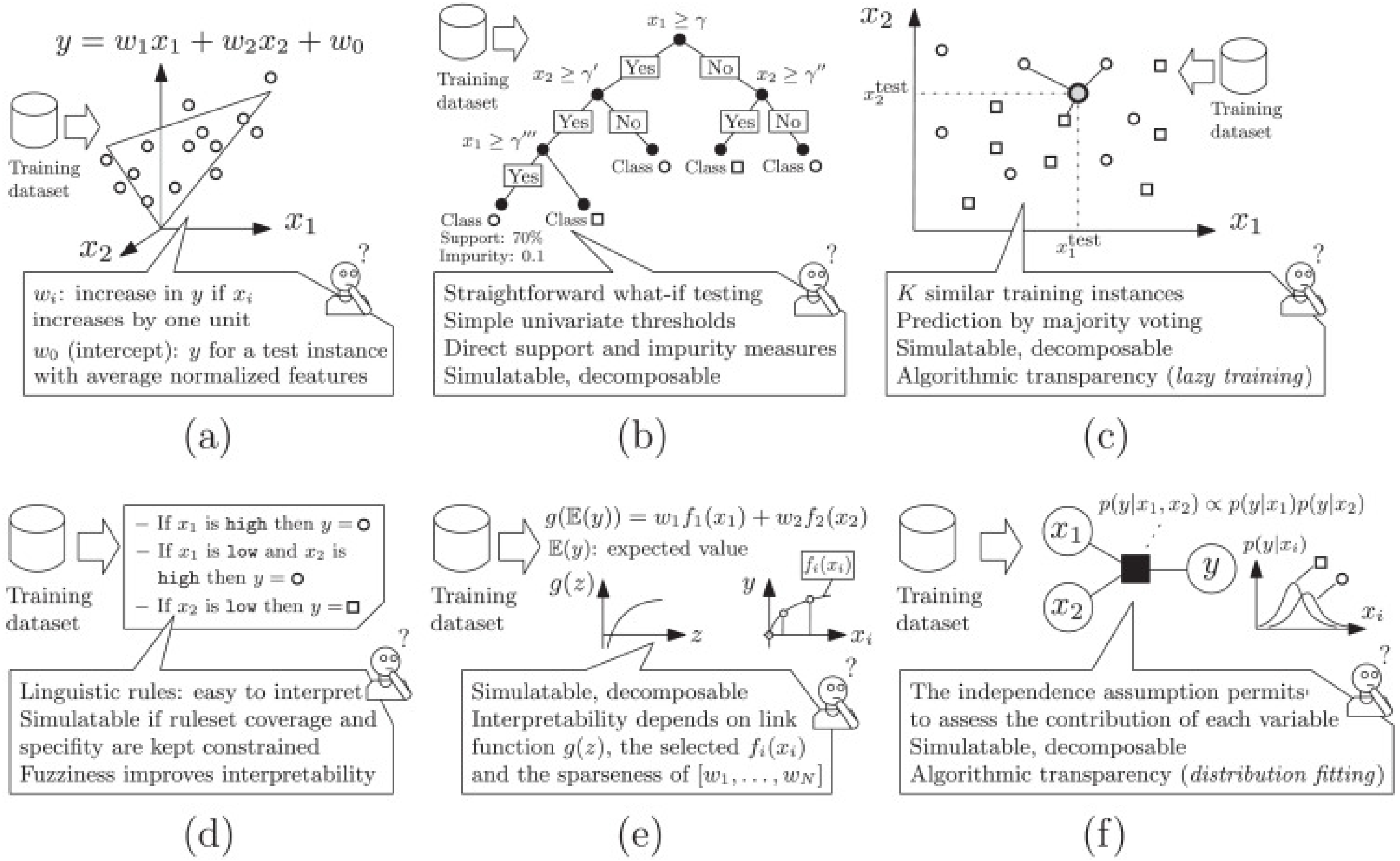
- Explanation must be based on **relevant information**!

- **Q:** “Why did Jane get the promotion (while Bob didn’t)?”
- **A1:** “Jane completed her project successfully and wore glasses.”
  - But John also completed his project successfully, and wearing glasses shouldn't affect the promotion decision.
    - That doesn’t explain why she got the promotion!

- But how do we decide that wearing glasses is not relevant, even if it might be **statistically significant**?

XAI in Various ML Models



(a) Linear regression; (b) Decision trees; (c) K-Nearest Neighbors;
(d) Rule-based Learners; (e) Generalized Additive Models; (f) Bayesian Models.

XAI Approaches

- **Post-hoc:**
  - Applied to already developed models in order to understand how one produces predictions for given input;
  - Prodice a separate algorithm which reads the end-to-end process.

- **In built:**
  - Build the decision-making algorithm so that traces have whithin them the basis for explanation.

Post-hoc Techniques: Model-Specific

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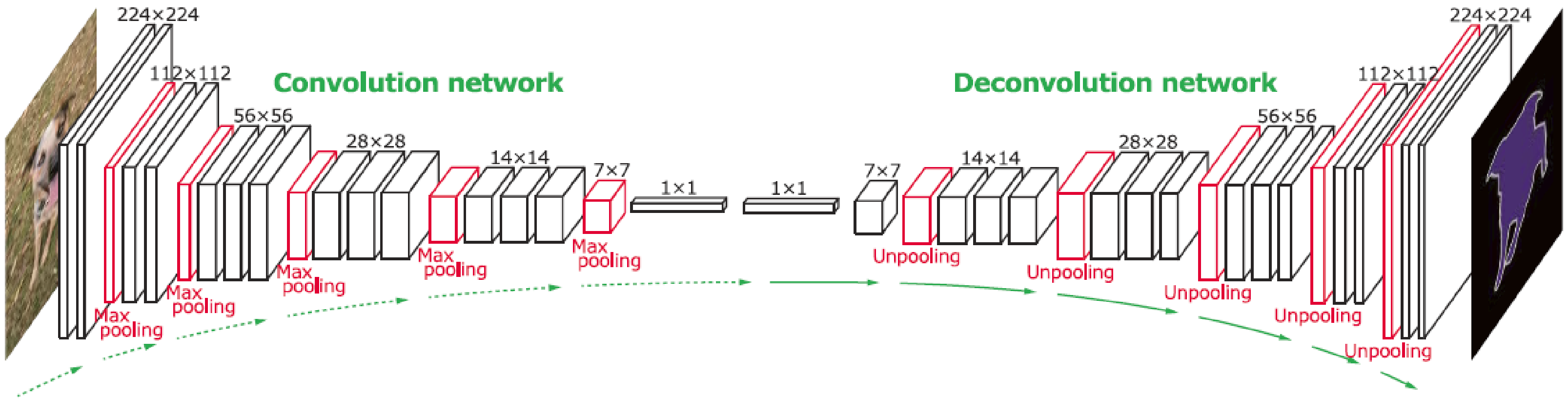
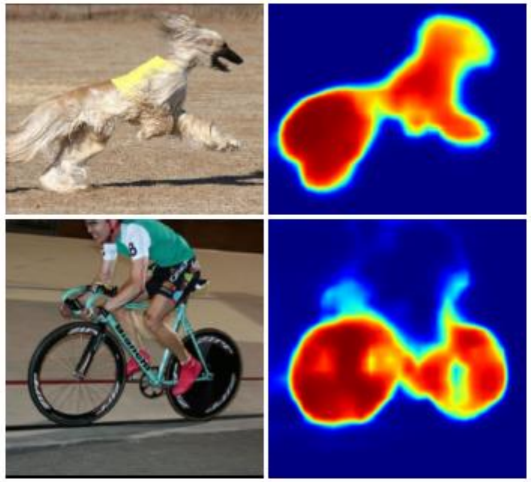
- Post-hoc approach can be categorized into two approaches: **model-specific** and **model-agnostic**;

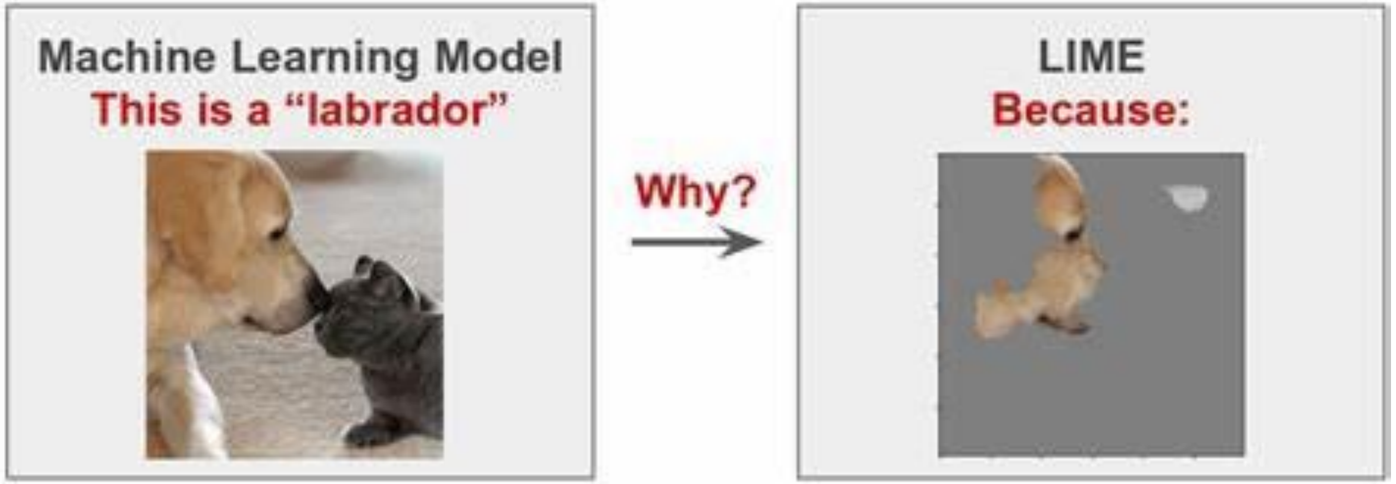
- One popular technique used in model-specific approaches is to **map back the output/prediction of a given input**, through the learned model, see which parts of the input were discriminative for the output.





Post-hoc Techniques: Model-Agnostic

- Techniques used in **model-agnostic** approaches (i.e. treat the original model as a **black box**) are categorized into two groups:
  - **Explanation by simplification** approaches aim to extract underlying rules or na approximate **interpretable model** from the original model.
    - “Local Interpretable Model-Agnostic Explanations” (**LIME**) system:



Post-hoc Techniques: Model-Agnostic

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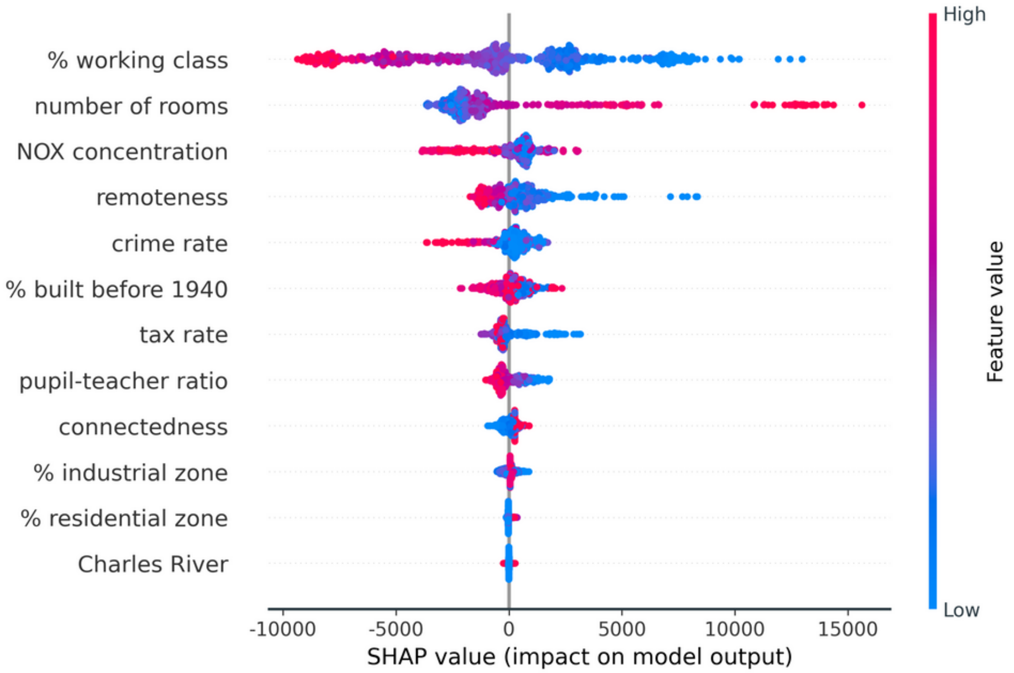
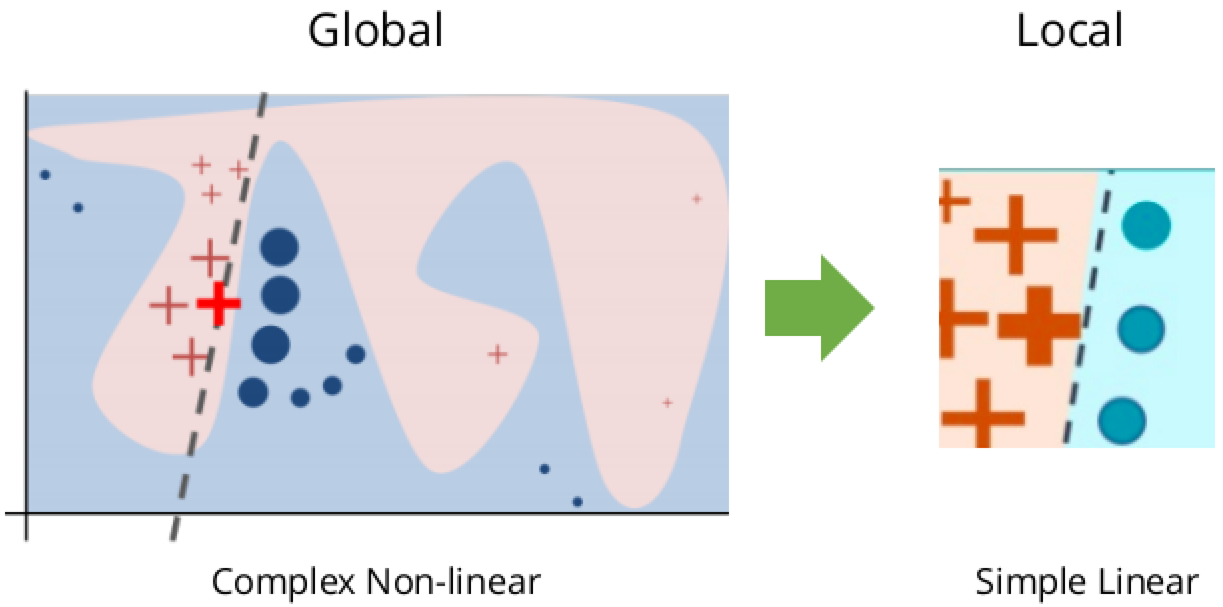
- Techniques used in **model-agnostic** approaches (i.e. treat the original model as a **black box**) are categorized into two groups:
  - **Feature relevance explanation** approach aims to describe the functioning of an opaque model by **measuring the influence and relevance of each feature** on prediction output.
    - "Shapley additive explanations" (**SHAP**) system:



Local Interpretable Model-Agnostic Explanations (LIME)

- LIME method was originally proposed by Ribeiro, Singh, and Guestrin (2016);

- The key idea behind it is to approximate a global model (which is a black-box) by **local models** which are simpler and transparent.



LIME Method

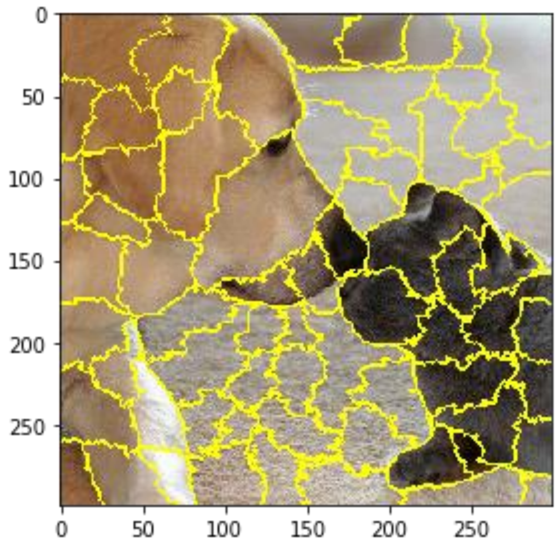
- In order to be model-agnostic, LIME can't peak into the model. What LIME does to learn the behavior of the underlying model is to first **perturb the input** (e.g., removing words or hiding parts of the image);

- For images, an original image is divided into interpretable components (contiguous superpixels).

Original Image

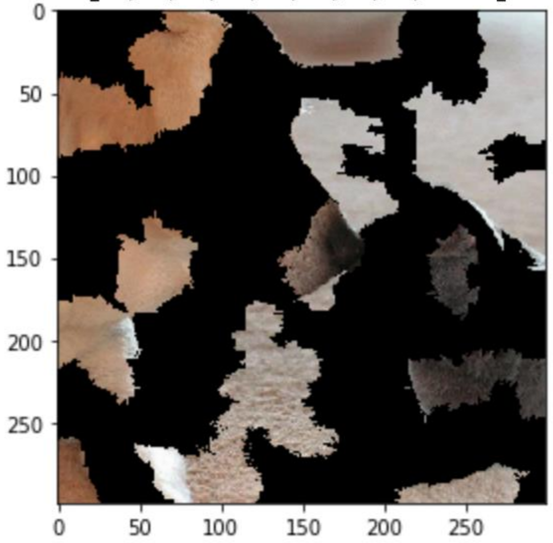
Interpretable Components

LIME Method

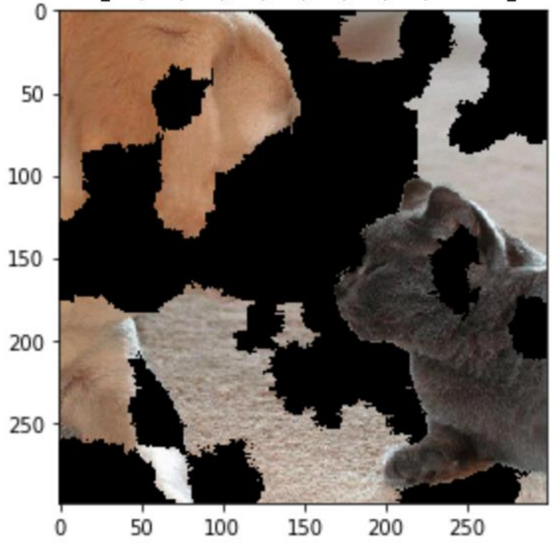


Original image segmented into 150 superpixels.

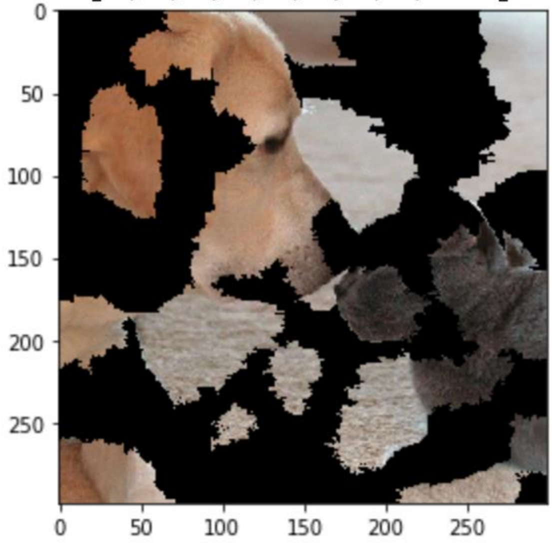
perturbation1=
[1,0,1,1,0,0,1,0,...]



perturbation2=
[1,1,0,0,0,1,0,1,...]



perturbation3=
[0,0,1,1,1,0,1,0,...]



LIME Method

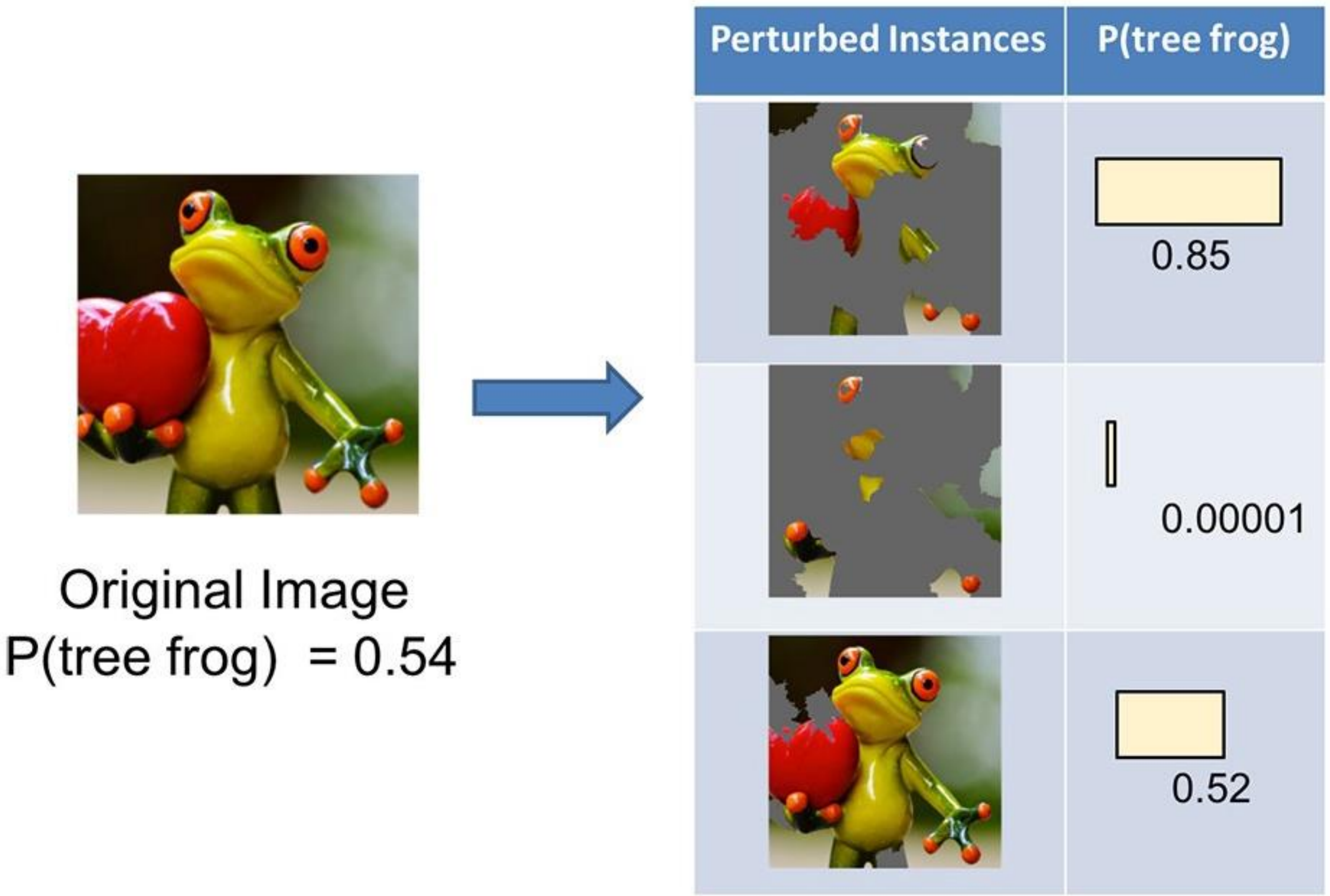
- **Perturbation for text data**:

  - For example, if we are trying to explain the prediction of a text classifier for the sentence:

    - “I hate this movie”, we will perturb the sentence and get predictions on sentences such as
      - “I hate movie”,
      - “I this movie”,
      - “I movie”,
      - “I hate”, etc.

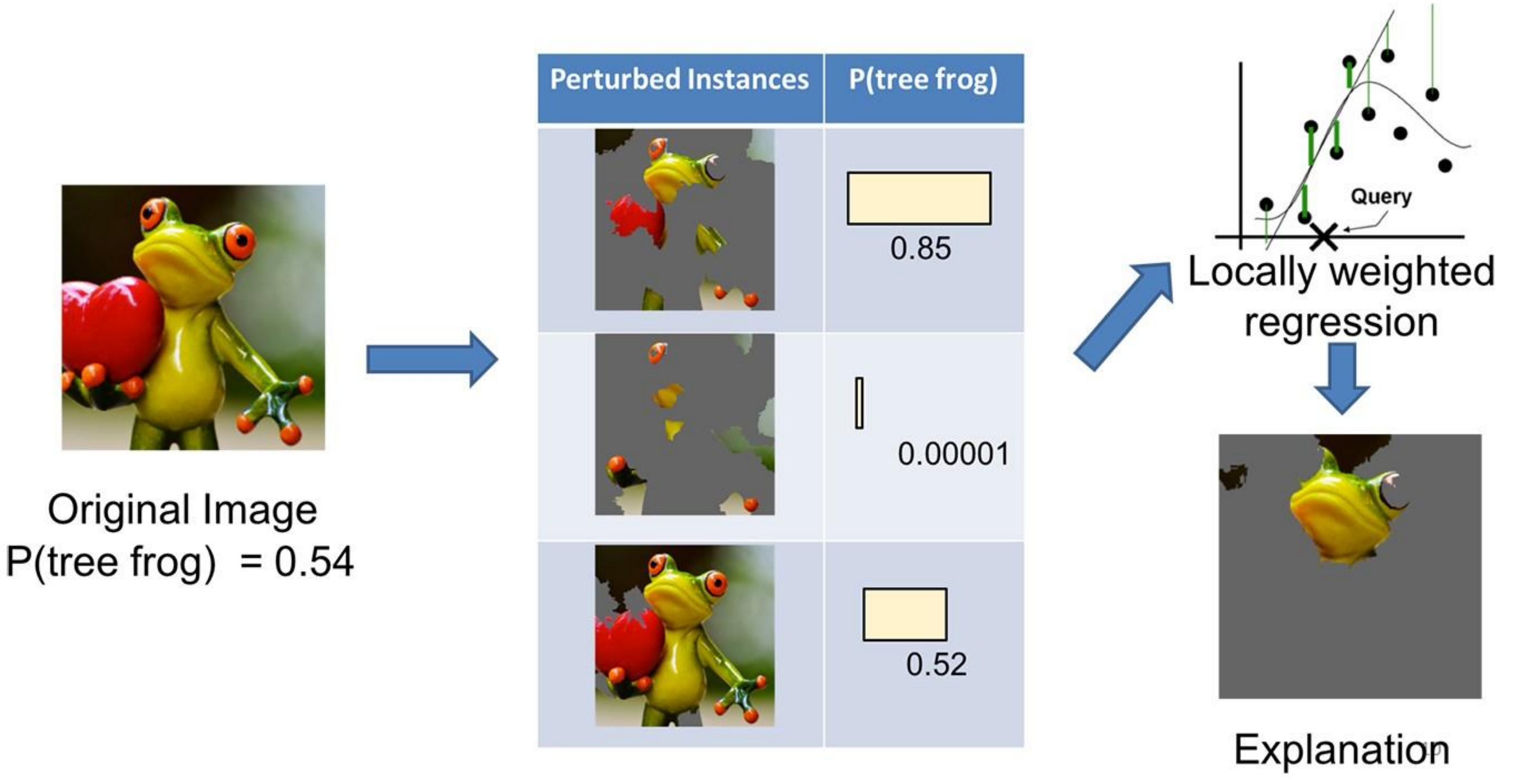
LIME Method

- Then LIME run the perturbed data in the model and see how the predictions change.



LIME Method

- Then LIME weights these perturbed data points by their proximity to the original example and learns an interpretable model on those and the associated predictions.



LIME Algorithm

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1. Sample the locality around the selected single data point uniformly and at random and generate a dataset of **perturbed data points** with it's corresponding prediction from the model we want to be explained.
2. Use the specified feature selection methodology to select the number of **features** that is required for explanation.
3. Calculate the **sample weights** using a kernel function and a distance function. (this captures how close or how far the sampled points are from the original point).
4. Fit an interpretable model (**locally weighted linear regression**) on the perturbed dataset using the sample weights to weigh the objective function (e.g. **squared error**).
5. Provide local explanations using the newly trained interpretable model.

SHapley Additive exPlanations (SHAP)

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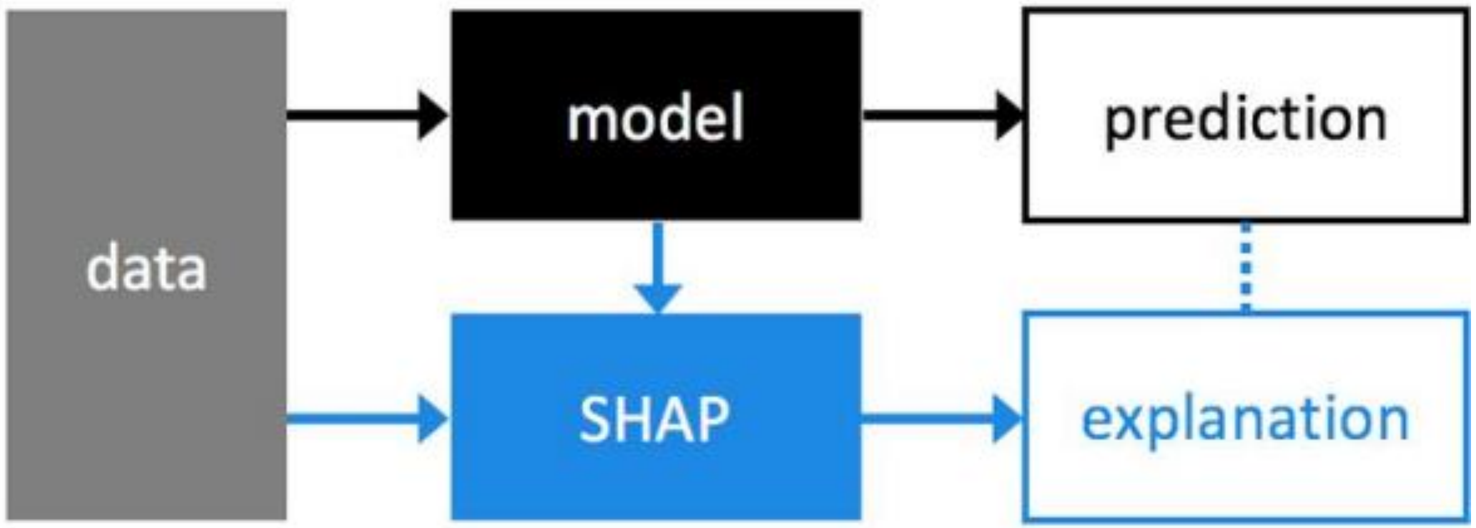
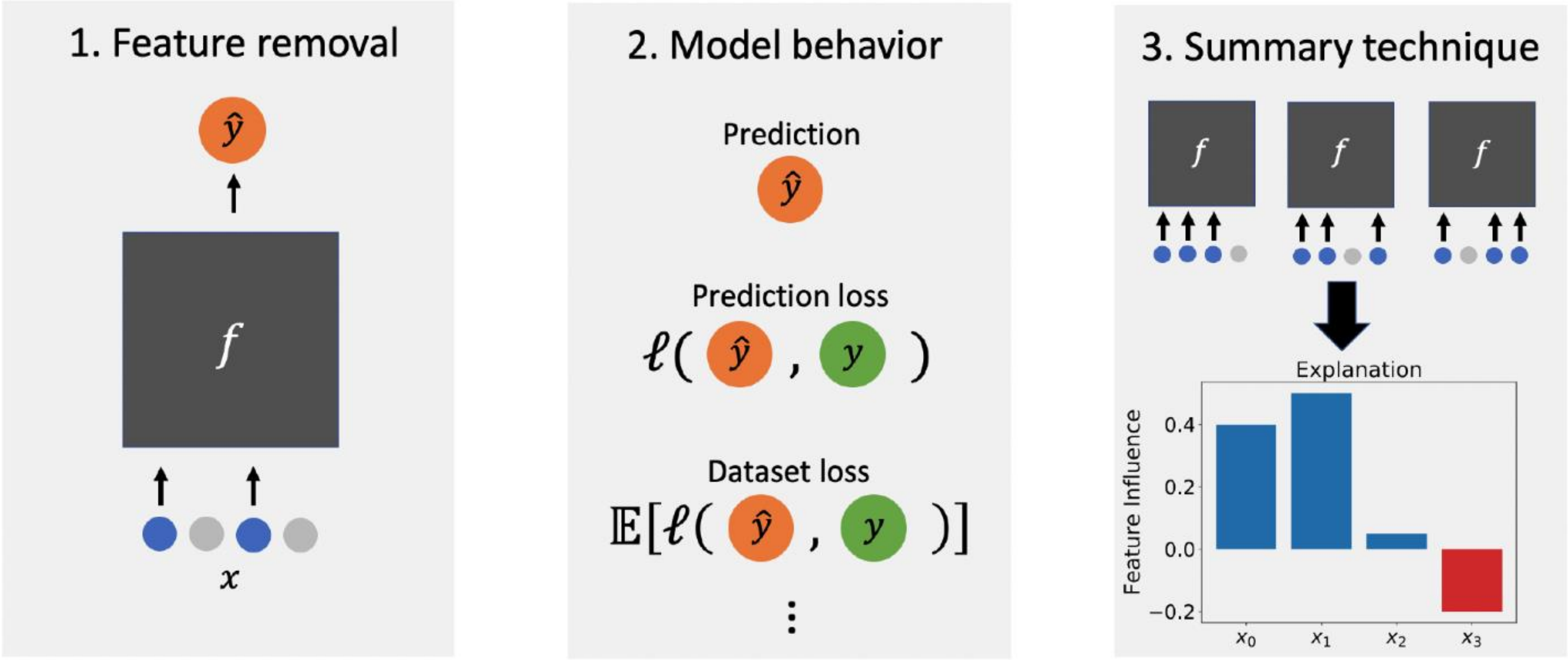
- Additive **feature attribution** method to explain the output of any ML model.



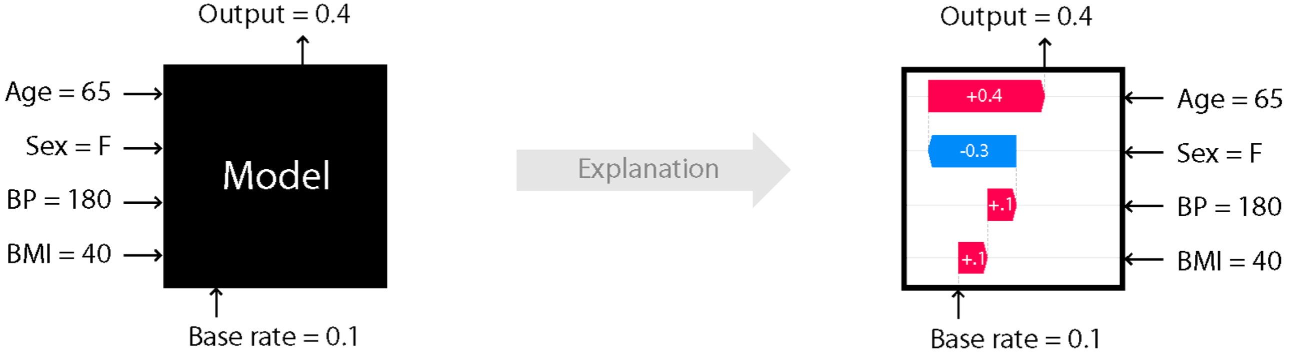
- It assigns each feature na importance value for a particular prediction.

SHapley Additive exPlanations (SHAP)

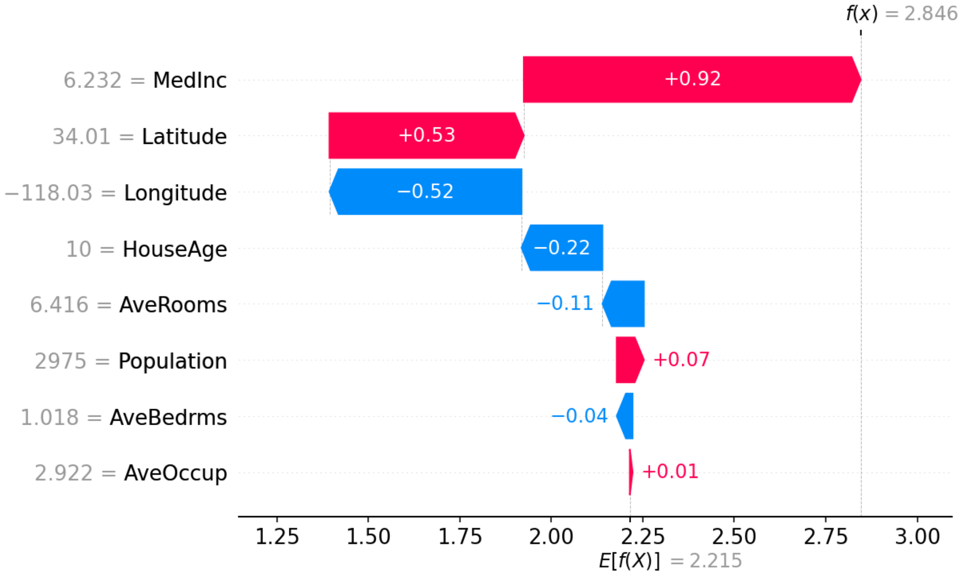
- The removal-based explanations framework



SHAP



Output = 0.4
Age = 65
Sex = F
BP = 180
BMI = 40
Model
Base rate = 0.1
Explanation
Output = 0.4
+0.4
-0.3
+.1
+.1
Age = 65
Sex = F
BP = 180
BMI = 40
Base rate = 0.1



f(x) = 2.846
6.232 = MedInc
+0.92
34.01 = Latitude
+0.53
−118.03 = Longitude
−0.52
10 = HouseAge
−0.22
6.416 = AveRooms
−0.11
2975 = Population
+0.07
1.018 = AveBedrms
−0.04
2.922 = AveOccup
+0.01
1.25
1.50
1.75
2.00
2.25
2.50
2.75
3.00
E[f(X)] = 2.215

Resources

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- Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). "Why Should I Trust You?": Explaining the Predictions of Any Classifier (Version 3). arXiv. https://doi.org/10.48550/ARXIV.1602.04938
- https://github.com/marcotcr/lime/tree/master
- Lundberg, S., & Lee, S.-I. (2017). A Unified Approach to Interpreting Model Predictions (Version 2). arXiv. https://doi.org/10.48550/ARXIV.1705.07874
- https://github.com/shap/shap