Intro to Neural Nets

Week 7: Interpretable ML
for Neural Networks

Today’s Agenda

Blackbox Models

- Tension between interpretability and performance.

Shapley Values

- Cooperative game-theory and idea behind Shapley values.

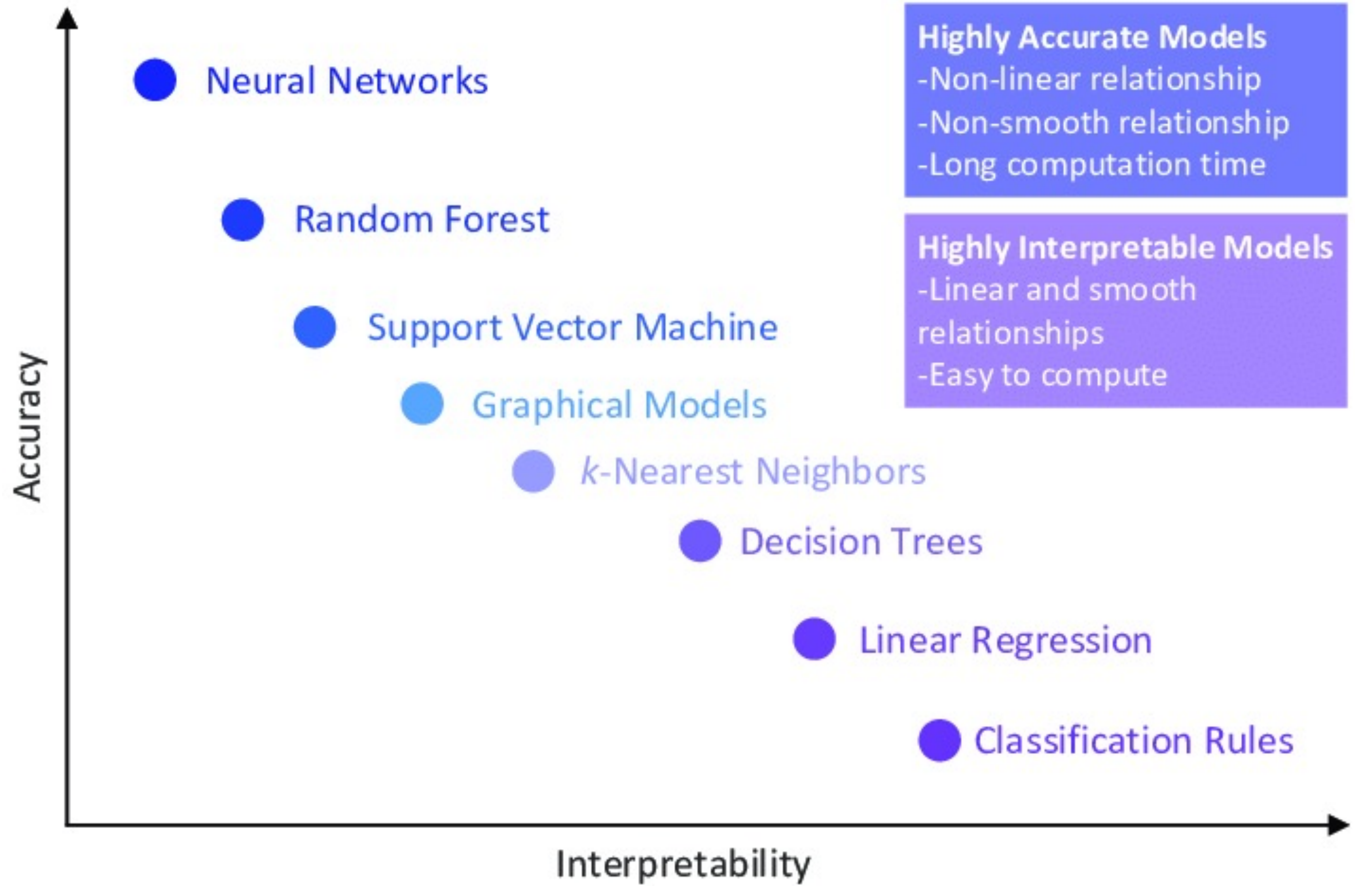
SHAP Library

- How we apply Shaply values to ML models.

LIME

- Alternative technique for estimating features’ marginal effects.

Tension: Interpretability vs Performance



Highly Accurate Models
-Non-linear relationship
-Non-smooth relationship
-Long computation time

Highly Interpretable Models
-Linear and smooth relationships
-Easy to compute

Shapley Values

Wikipedia:

The Shapley value is a solution concept in cooperative game theory. It was named in honor of Lloyd Shapley, who introduced it in 1951 and won the Nobel Prize in Economics for it in 2012. To each **cooperative game** it assigns a **unique distribution** (among the players) of a **total surplus** generated by the coalition of all players. The Shapley value is characterized by a collection of desirable properties.

More Simply:

What is the marginal contribution of each player across all possible coalitions?

Note on Game Theory

Background:

Two main types of games: **non-cooperative** and **cooperative**. Non-cooperative games involve competing players, whereas cooperative involve collaboration for mutual benefit.

Some games involve competitions between coalitions.

Game? Players? Payoff?

Link to Machine Learning Models

The analog for these notions in ML is as follows:

- The **game**: the prediction task.
- The **players**: feature / predictor *values*.
- The **total surplus** (payoff): the predictions the model yields under a particular coalition (combination) of feature values.

Let's work through a simple example in a traditional cooperation context, and then come back to the machine learning models.

Shapley Value Example

Escape Room:

Imagine we have **three players: A, B, and C**, who decide to spend the weekend playing several different escape rooms around the city. The players participating in each room vary, however, because each has some errands to run over the course of the day.

The **players earn a reward (payoff)** for completing an escape room, and they then share the proceeds. The faster the players complete a room, the more money they earn. It is quite likely that the **players do not contribute equally** to the task. Some players probably have more experience than others, they know the subject matter matter for the puzzles in any given escape room, or they may just be more (less) interested in the game.

How should we split the reward between the players?

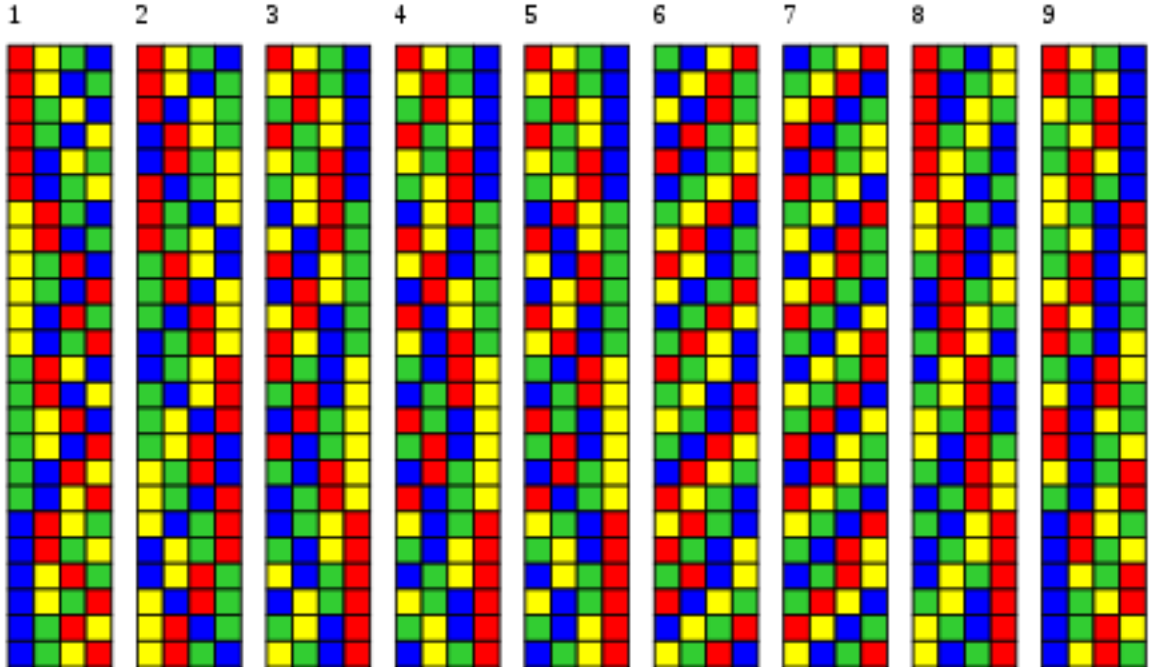
Shapley Value Example

Coalitions and Payoffs:

1. When playing alone:
   - A: \$80
   - B: \$56
   - C: \$70

2. When playing in pairs:
   - A + B: \$80
   - A + C: \$85
   - B + C: \$72

3. When all together:
   - A + B + C: \$90



Shapley Value Example

Examples of Average Marginal Contribution:

- A plays alone = \$80 (marginal contribution of A = \$80)
- B joins A = \$80 (marginal contribution of B = \$0)
- C joins A and B = \$90 (marginal contribution of C = \$10)

- A plays alone = \$80 (marginal contribution of A = \$80)
- C joins A = \$85 (marginal contribution of C = \$5)
- B joins A and C = \$90 (marginal contribution of B = \$5)

Simply Put:

We look at all permuted sequences of players, and then average over the resulting marginal contributions.

Shapley Value Example

Average of Marginal Contributions:

- When we average over each player’s marginal contributions (note, on the right, the marginal payouts are ordered by A, B, C)…

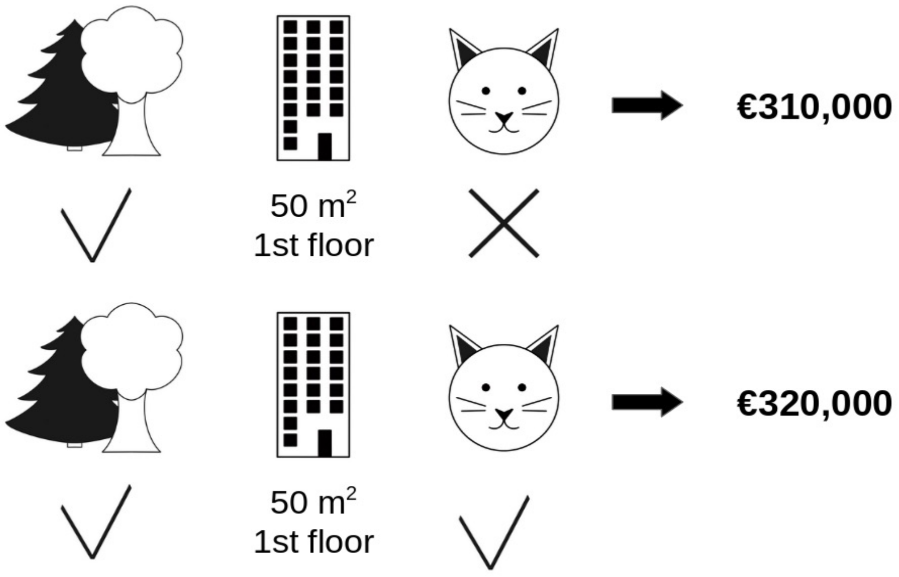
(A, B, C)	$(80, 0, 10)$
(A, C, B)	$(80, 5, 5)$
(B, A, C)	$(24, 56, 10)$
(B, C, A)	$(18, 56, 16)$
(C, A, B)	$(15, 5, 70)$
(C, B, A)	$(18, 2, 70)$

… we find that A contributes an average of (80 + 80 + 24 + 18 + 15 + 18) / 6 = 39.167, B contributes an average of 20.667, and C contributes an average of 30.167. These are our payoff weights, e.g., A contributes ~ twice as much as B.

SHAP: SHapley Additive exPlanations

Prediction Scenario:

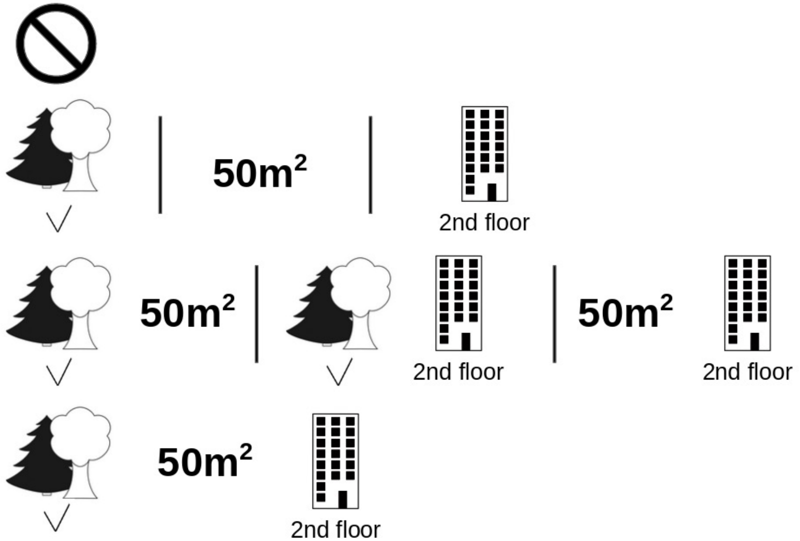
- We have a machine learning model that predicts some label.
- We have many games, i.e., the predictions the model produces for each observation.
- We thus have different coalitions of players, i.e., combinations of feature-*values*.
- Note that the average marginal contribution for a feature could be negative here.



SHAP: SHapley Additive exPlanations

Procedure – Marginal Contribution of ‘Pets Allowed’:

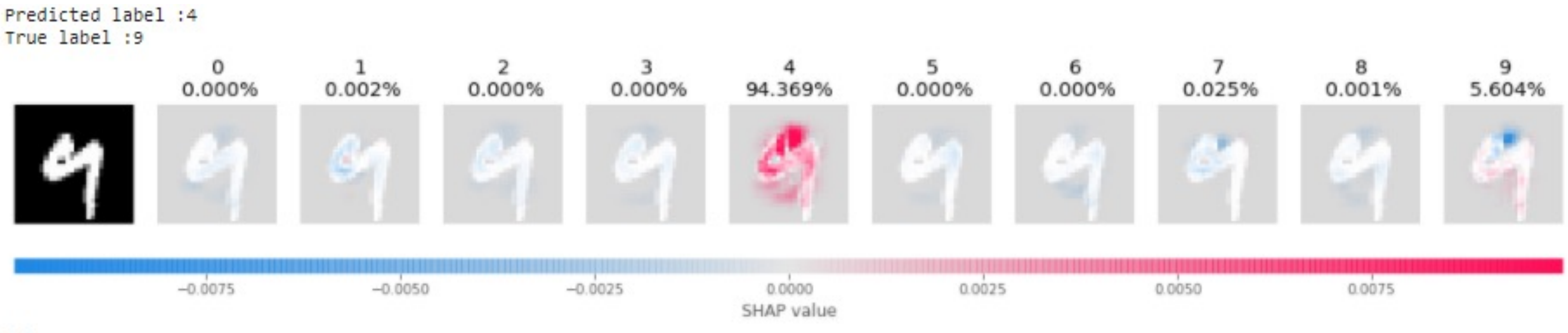
- We can cycle through all permutations of feature-values, just like in the escape room example.
- For a given feature value, we can randomly replace it with some other value from the data. Additionally, we can randomly replace other feature values with alternatives from the data.
- If we consider enough ‘counterfactuals’, we gain a sense of how ‘moving across a feature’s values’ affects the marginal prediction, under many combinations of *other* feature values (partners).



SHAP: SHapley Additive exPlanations

Marginal Contribution of a Pixel:

- In a CNN, our input predictors are pixels. We can do the same thing here using pixel values.
- We can figure out a Shapley value for a particular pixel position, in a particular color channel, for feature values that range from 0 to 255.
- To simplify the problem, we might also work with super-pixels (group pixels, averaging their feature-values).

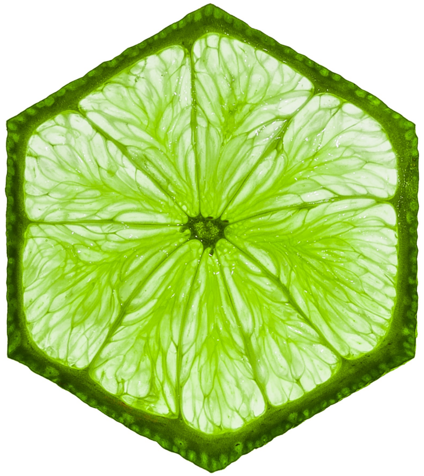


Local Interpretable Model-agnostic Explanations

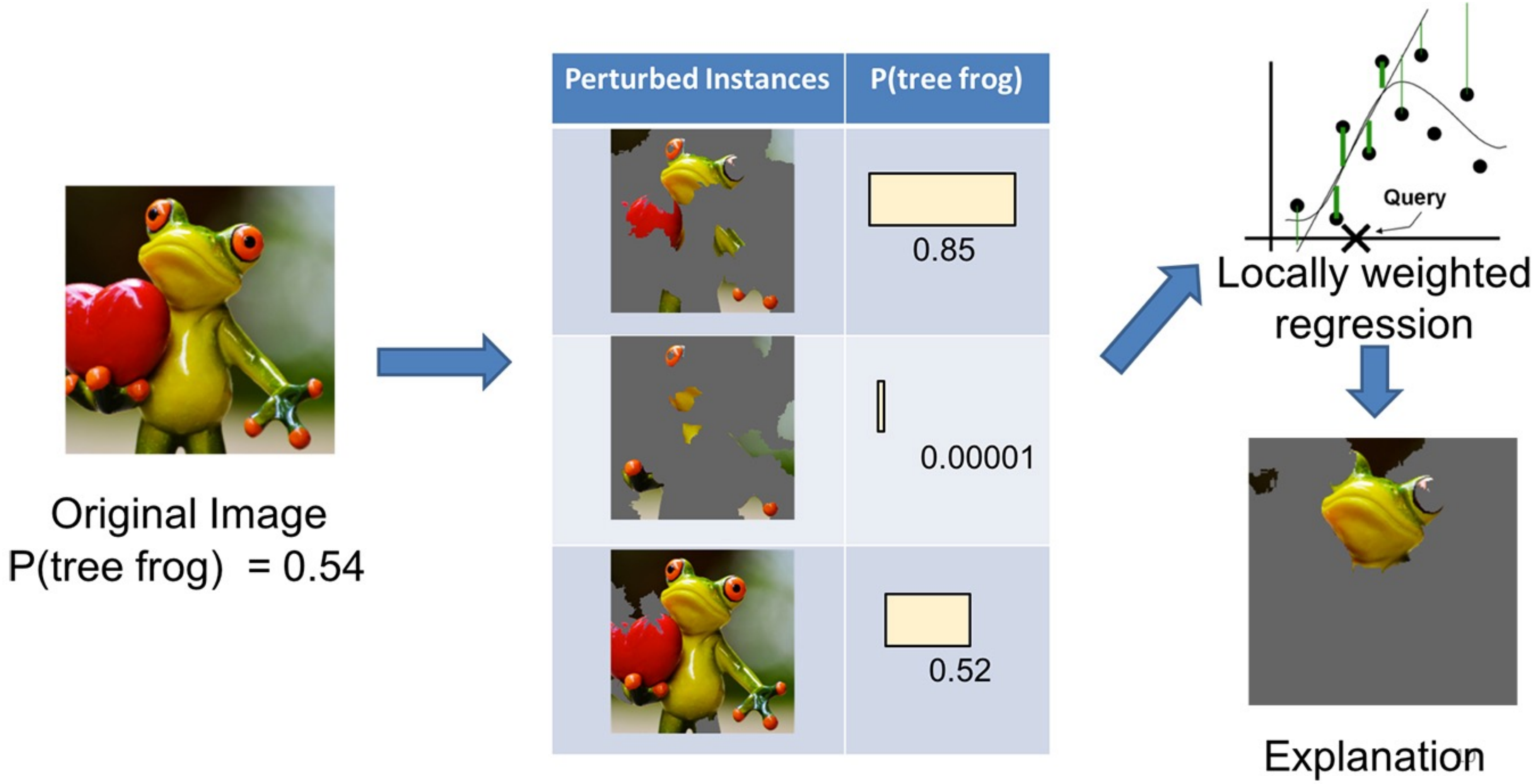
Procedure – Local Perturbations of the Data:

- We assume that a features' contributions to the prediction can be locally approximated by a linear regression. Then:

  1. For a given prediction, **randomly perturb the observation** (modify its feature values), repeatedly, and **recover the associated predictions** for each synthetic observation.
  2. This procedure **yields an observation-specific dataset**. Use the dataset to **estimate a weighted linear regression** on the dataset, weighting observations inversely by their distance / dissimilarity from the original observation.
  3. **Beta coefficients** reflect features' localized marginal contributions to the prediction.



Local Interpretable Model-agnostic Explanations



Original Image
P(tree frog) = 0.54

Perturbed Instances	P(tree frog)
	0.85
	0.00001
	0.52

Locally weighted regression

Explanation

Questions?