XAI on Reinforcement Learning: Explaining Tic Tac Toe moves

Data Mining and Machine Learning

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Introduction

Introduction

- Tradeoff between performance and explainability of ML models
- · Many "real-world" decisions have to be explainable
- · Other decisions have not to be explainable but it helps trusting the model

Introduction

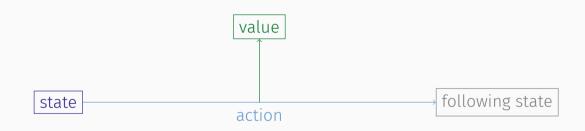
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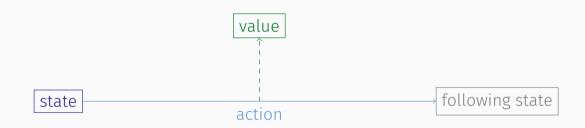
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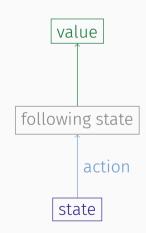


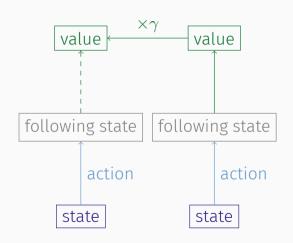
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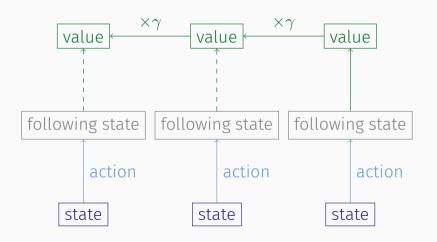
Backgrounds

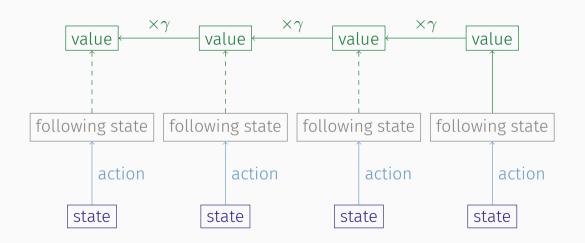












Tic Tac Toe - Architecture

- State is encoded as Vector of size 18
 - · "1" means that a field is taken, "0" means that it is free
 - First 9 fields represent the game field of the first player
 - Other 9 fields represent the game field of the other player
- Action is encoded as a vector of size 9
 - Field with the highest value is used as action
- Values are applied in training in a way that the action should have the specified value for the state

Tic Tac Toe - Architecture

- It is possible to choose between several opponents:
 - · Random does any random turn (that turn might be invalid)
 - · Easy does any valid random turn
 - · Medium does any valid random turn and wins when possible
 - Hard does any valid random turns, wins when possible and avoids the opponent to win when possible otherwise
 - Optimal implements a backtracking algorithm (minimax) and plays optimal (wins or plays a draw)
 - · Network uses the trained network to do turns

eXplainable AI (XAI)

- Goal: Explain decisions of a neuronal network in a way that is understandable by humans
- · Distinction by the time the explanation is created
 - · Post-Hoc: Explanation is created after the network has done the prediction
 - Intrinsic: Explanation is created while the network does the prediction
- · Distinction by relation to the model
 - Model agnostic: Independent of the model, generates inputs and uses model outputs for calculation (black box)
 - **Model specific**: Dependent of the model, uses its inner workings for calculation (*white box*)
- Distinction by explanation scope
 - · Global: Explains the model for all possible inputs
 - · Local: Explains the model for one specific input

Tic Tac Toe and XAI

- **Hypothesis**: There should be exactly one explanation for a decision made by a deterministic algorithm. Everything else is not an explanation but an interpretation.
- Initial idea: Use multiple explanation algorithms to explain the same decision and verify if the return the same explanation

Tic Tac Toe and XAI

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- · Workaround: Use a modified version of LIME and manually implement it

Local Interpretable Model-Agnostic

Explanations (LIME)

Local Interpretable Model-Agnostic Explanations (LIME)

- · Can be used to identify "relevant" parts of images
- Split the image into parts and conduct the prediction for the single parts ("remove" other parts)
- If the predicted probability for the class is higher than for the entire image, that part can be marked as "relevant"
- Explaination is the combination of all "relevant" parts

- · The state of the game is used in input
- The output is a list of action probabilities
- · Idea: Generate "other versions" of the sate and predict the action
 - · Set the fields that are used by the player or the opponent to "empty"
 - · Query the prediction for each generated "other version" of the state
 - add the predicted value of the resulting state to the sums of all state fields that were active (weight with the distance to the original input)
 - · Normalize the results

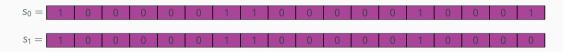




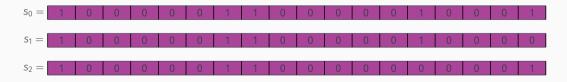




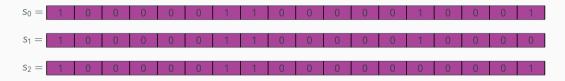




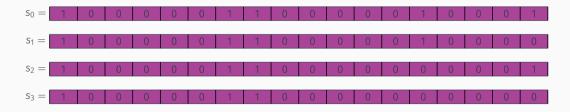




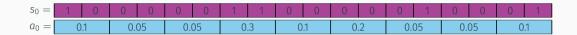


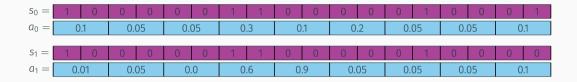


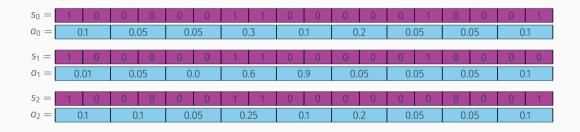


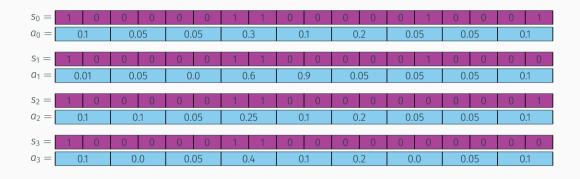


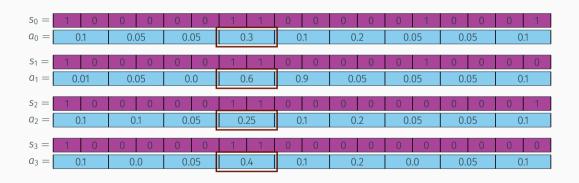


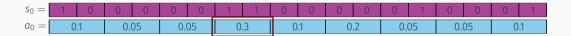


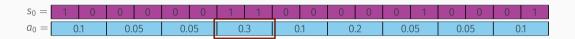




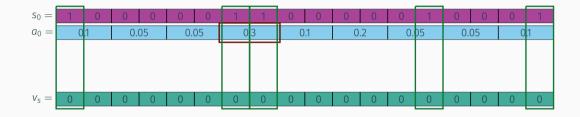


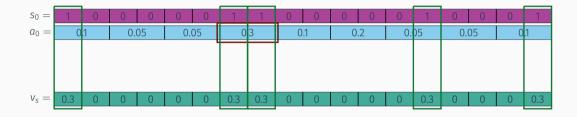


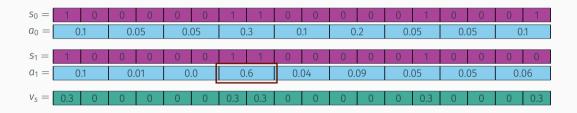


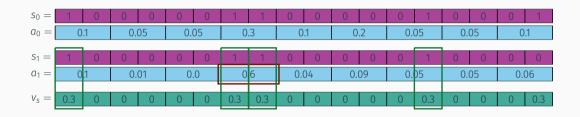




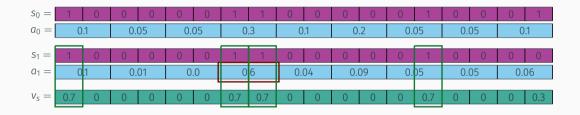


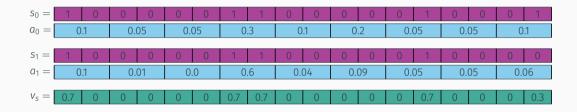


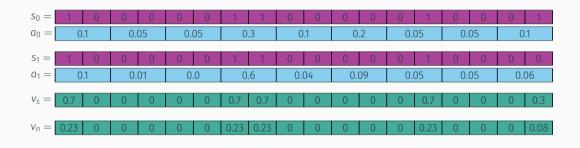










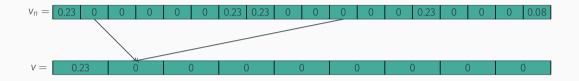


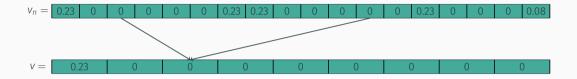


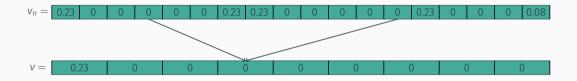


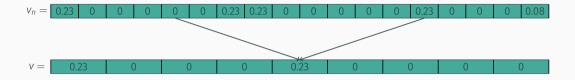


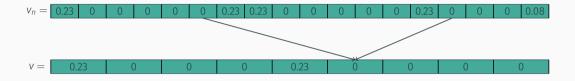


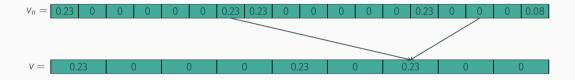




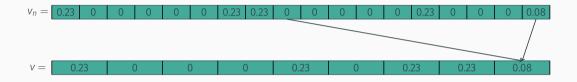














V =	0.23	0	0	0	0.23	0	0.23	0.23	0.08

Demo 1

Does this work at all?

Demo 2

Inspect the ML model

Questions?

References i

1] Randall Munroe. Machine Learning. URL: https://xkcd.com/1838/ (besucht am 11.01.2022).