Hexapawn – Playing chess against a matchbox computer to grasp the feedback principle underlying machine “learning” - AI unplugged 3

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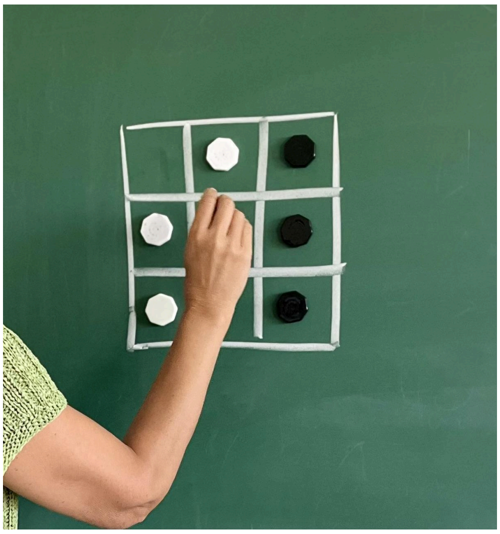

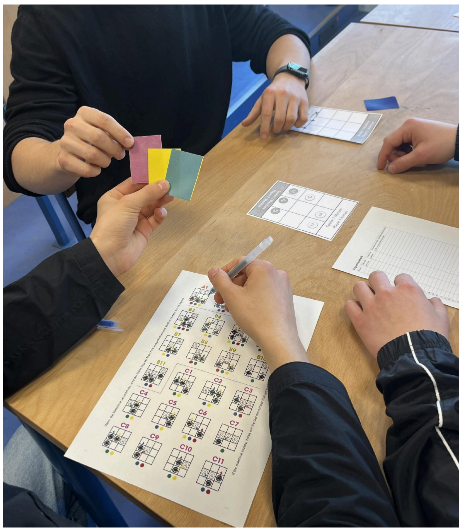

Short description of the practice

Hexapawn is a hands-on way to introduce concepts of algorithms and artificial intelligence (AI). The simple 3×3 board game, originally invented by Martin Gardner, illustrates the principle of negative feedback which underlies backpropagation within current machine “learning” systems. It only uses pawns that move and capture like in chess, making the rules easy for pupils to grasp. There are many levels on which this intervention can be useful:

a) Helping learners develop their understanding of feedback as a fundamental principle of machine “learning”, that a machine (or even a simple matchbox model) can "learn" from mistakes and improve.
b) Understanding the difference between subcategories of AI (expert rules-based systems versus machine “learning”)
c) Experiencing one's own learning process and reflecting on what machine “learning” is, and above all, is NOT. This seems especially relevant to avoid unsubstantiated anthropomorphisms when working with and thinking about AI. Therefore, we have used Hexapawn both with pupils directly as well as in training their teachers and parents.

Hexapawn is part three of the HERMMES AI unplugged (AIU) series of practice examples.

Age span of children/adolescents

12 - 15 years
15-18 years
18+ years

Target group

Pupils/students
Educational staff
Parents/caregivers

HERMMES curriculum areas

COMPUTATIONAL THINKING (CT) AND PROBLEM SOLVING

ICT: CT, problem solving
Operate and apply / technical understanding

CRITICAL INFORMATION AND DATA LITERACY

Analyse and (self)-reflection

DESCRIPTION AND USE OF THE PRACTICE

Work instructions and roadmap

Time learners need for the practice

90 minutes – up to 180 minutes or even 270 minutes for target groups with little chess experience. More if you want to explore differences between humans and machines.

Group size

~30 participants

Preparation time for teacher/facilitator

~60 minutes

Location / setting / specific circumstances

Tables or smaller flat surfaces for small chessboard-sized space needed

Necessary equipment and materials

For the presenter or teacher:

- Blackboard or another magnetic surface (for example a flip-chart base)
- Chalk (white, red, green, blue, yellow) or wipeable marker pen (black, red, green, blue, yellow)
- Three black and three white large round magnets

For each group of two to three participants:

- One 3 x 3 board with three black and three white pawns
(different options to make this, see preparation section below)

- One Hexapawn computer (different options see preparation section below)
- one printout (see appendix) of instructions for “human player”
- one printout (see appendix) of instructions for “machine operator”
- one printout of instructions for the game supervisor, plus a table for documentation of results (how often does black or white win?)

Detailed description

Hexapawn is a hands-on way to introduce concepts of algorithms and AI. The simple 3×3 board game, originally invented by Martin Gardner, illustrates the principle of negative feedback which underlies backpropagation within current machine "learning" systems. It only uses pawns that move and capture like in chess, making the rules easy for pupils to grasp. There are many levels on which this intervention can be useful:

d) Helping learners develop their understanding of feedback as a fundamental principle of machine "learning", that a machine (or even a simple matchbox model) can "learn" from mistakes and improve.
e) Understanding the difference between subcategories of AI (expert rules-based systems versus machine "learning")
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Hexapawn is part three of the HERMMES AI unplugged (AIU) series of practice examples.

Machine "learning" constitutes one of the fields of AI. Very simply put, on the one hand, there are expert systems, where the algorithm does not change after it is established and is based on the knowledge of a human expert. On the other hand, machine "learning" involves training an algorithm on the basis of data, enabling it to improve its performance over time, which can be called "learning", put in parentheses as it is not learning in the human sense, but a statistical optimisation process.

Background

In educational settings, the challenge is how to introduce a complex topic such as AI in a way that does not cause pupils more confusion than clarity, particularly since the programming of algorithms and the learning processes themselves are usually not easily understood without prior knowledge of programming. Schwill (1993) calls for selecting *fundamental ideas* from computer science and supporting learners in grasping these. Consistent with this strategy, Martin Gardner, who published numerous articles on mathematical games over many years, had already introduced a simplified version of chess involving six pawns, which he called Hexapawn as early as 1962. The game is played using 24 matchboxes, or other simpler setups described in the materials section. The matchbox-based computer "learns" from each game it loses. Over time, it improves to the point where the human player can no longer win.

Due to its transparent and mechanical nature, Hexapawn offers a valuable way to illustrate the fundamental ideas behind machine "learning". Furthermore, the activity provides an opportunity to engage in broader discussions about the nature of learning itself, and the extent to which self-awareness (which does not exist in a matchbox computer) plays a role in these processes.

Overview of the activity

In the following sections, we describe in a detailed way on how to work with Hexapawn that puts a focus on comparing the way pupils learn to win Hexapawn to the way the matchbox computer does. But if you are familiar with these kinds of activities, you can get a good overview via this video that focuses on phase 2 and 3 of the process described below: https://www.youtube.com/watch?v=FhI3BxPqNss&t=12s

This Hexapawn practice is part three of the HERMMES AI unplugged series. We recommend carrying out parts one and two first, and parts four and above afterwards.

Texts below that are in italics are optional for a focus on anthropo- and technomorphisms

In the following, text in italics indicates a focus on differences between machine "learning" and holistic human development and learning processes, that is also the overarching and more philosophical aspects of contesting anthropomorphisms and technomorphisms. If you want to put the focus only on the computer science aspects of the intervention, you can leave out these italicised parts.

To work with pupils, it makes sense to work with Hexapawn in six steps. Here is a brief overview:

Overview of all 6 steps

Step 1&2: After a preparation phase (teacher only), the pupils get to know the game by playing against each other until they have mastered the relatively simple game. In this way, they understand how the rules are applied and how to win a*nd to reflect on their strategies for learning to win*. If you are working with mathematically advanced pupils, you can skip or considerably shorten step 1.

Step 3: In the second phase, the computer is introduced and learners experience how it makes its moves using randomness. Learners play a few more rounds until they are familiar with this principle. However, in this phase no "learning" is taking place yet. Whether the computer wins or not depends on chance.

Step 4&5: Now strategies for improving the computer's performance are introduced. Changing the setup according to the knowledge of an expert human Hexapawn player is one way of doing this (corresponding roughly to rule-based expert systems). Another way, representing a simplified version of machine "learning", would be to change the setup (removing a bead from a matchbox) as a reaction to a mistake that was already made, so that this cannot be repeated again in the same situation. (Feedback/back propagation as a principle used in machine "learning").

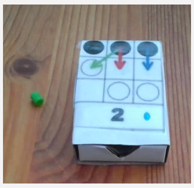
***Step 6&7**:* Finally, the differences between human learning and machine "learning" can be discussed briefly, or more thoroughly. *Anthropomorphisms and technomorphisms can be mentioned either in a more top-down manner of wanting to reduce them, or a more process-oriented manner of exploring them and relating them to one's own conceptions* *and beliefs as a learner – or (future) teacher.*

Preparation

1. Build matchbox computers

Version A

The “computer” consists of 24 emptied matchboxes with labels on the outside of the box, an opening cut into a part of the box, and small coloured beads inside (print out page “Hexapawn 24 matchboxes” in colour on self-adhesive A4 papers, cut and paste these to empty matchboxes). In total, 24 green beads, 21 red, 8 blue and one yellow bead are needed.



It is possible to order empty small boxes without matches here in Germany: https://basteln-de.buttinette.com/shop/a/pappschaechtelchen-weiss-5-2-x-3-6-x-1-5-cm-20-stueck-602826. But you ask the school community to collect empty match boxes (ideally of the following size: 5,2 x 3,6 x 1,5 cm).

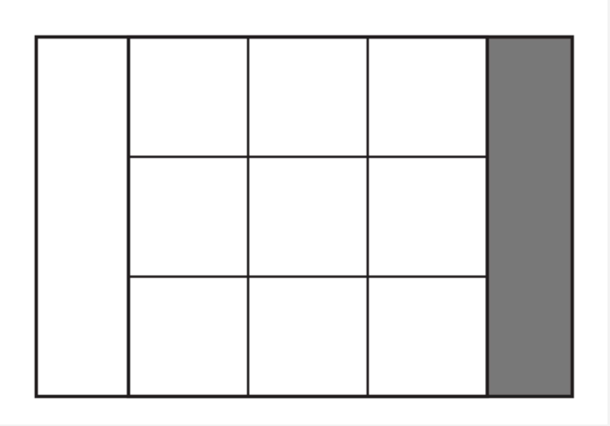
Version B

The “computer” is a card game, see the details below (printout hexapawn A attached at the end of this PDF).

Version C

the “computer” is a single A4 printout hexapawn B. Additionally, each group will then throw a die.

2. Print out all necessary handout sheets (one for each group of three pupils).
3. Print out or draw chessboards on cardboard.
4. Build or buy black and white pawns (eco-friendly version is to cut from wooden branches or buy the game of Go, Gobang or Gomoku in a second hand shop) - three white and three black pawns are needed for each team of two to three learners.
5. Place on each table for two to three learners the following items:
    a. a chessboard (3x3),



b. Three white and three black pawns.

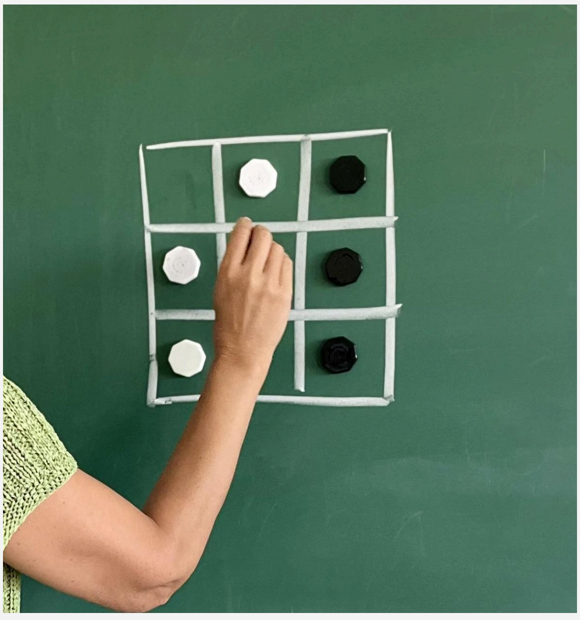
Step 1. Human vs. human – learning to play

At the beginning, the goal is simply to become familiar with the game. Start by introducing it with the board and explaining the rules. Explain how pieces are allowed to move and capture, and what conditions lead to a win.

Depending on the skills in chess gameplay and computational thinking of the target group, this step can take more or less time, anything between 40 minutes for young pupils and less than 5 minutes for MINT students at university level.

If you want to give a slow introduction for learners with lower skills, we recommend this procedure:

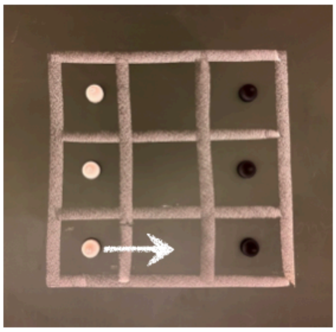
- Draw the 3 x 3 board on the blackboard (or on another magnetic surface, most flipchart stands have a magnetic surface). Place the magnets on the board in the starting position. Ask the learners if anyone has experience in playing chess. Declare that you will play white and ask one of them to play black.



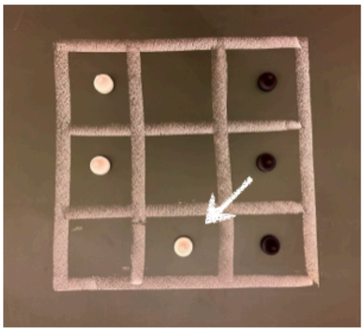
- Demonstrate the two different options for moving the pawns with the magnets.
    - Like pawns in chess, pieces can only move straight forward, while captures must be made diagonally. In the first move of white, as there is no opponent near, only the straight forward move is possible.
- Write short reminders of the rules onto the blackboard

  “move forward”

  “capture diagonally” (no “must-capture”)
- Introduce a convention: **White starts**. This is very important as the Hexapawn computer will later make only the moves of the black player with white starting.



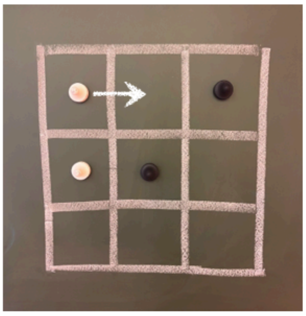
Move forward



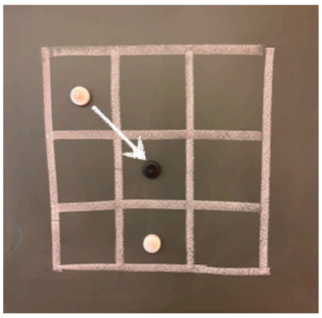
Capture diagonally

Introduce the rules for winning while you play: A player wins, when:

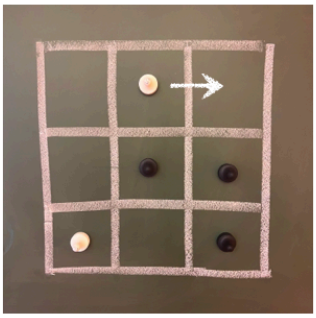
- the opponent is “blocked”, namely its opponent’s turn has no legal moves left,
- all of the opponent’s pieces are captured, or
- one of their own pieces reaches the opponent’s back row (this is similar to “making a second queen” in chess)



Block opponent



Capture all pieces



Reach opponent’s side

It is helpful to leave these rules visible on the whiteboard or blackboard so pupils can refer to them. Alternatively, print out rules of the game and hand them out.

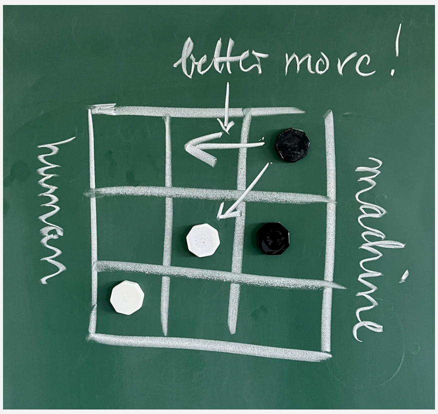
Afterwards, allow the pupils to play a few rounds in groups of two (each group gets one board and three white and three black pawns). The pupils can practice and become comfortable with the rules.

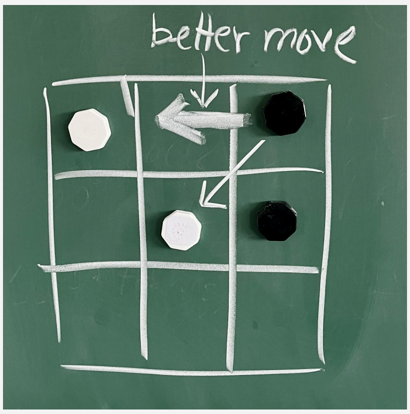
Ask guiding questions and recruit co-teachers

Walk around the groups and ask them who has been winning more: black or white. Usually, this will be answered as “both wins equally often” in the beginning. If you find a team that responds that black wins more often, stay with them. They will often say the following: “we are not sure if white can win, recently we have always had black win, provided black plays well.” This will often be the case with quick mathematically talented learners. You can then ask them questions that help them and guide them step by step towards the **conclusion that in fact, black always wins when playing optimally**. Once they have grasped this firmly, you can ask them to become your co-teachers and ask other teams of players the same leading questions and provide the same step-by-step guidance. It is crucially important to tell co-teachers: NOT to spoil the fun of learning by simply telling other less advanced learners the conclusion!

Here are suggestions for guiding questions that can speed up reaching the conclusion:

- Ask what is meant by “playing well”, and they will often answer that it means anticipating the possible reactions of the opponent when choosing the next move. In other words: thinking ahead one or even more moves.
- Ask them if they can show you a sequence of moves that lead to white winning. Any attempt for this is quickly abandoned with the first white move being a pawn on one of the sides. Moving the middle pawn appears more promising. There are often two remaining positions that many pupils think are a way for white to win:





Option A Option B

- Show several positions where failing to capture your opponent’s central pawn on move two or three leads to a loss. In such cases, choosing the “capture” option is better than simply making another move.
- BUT: There can be an overgeneralisation of this rule that runs: ALWAYS capture if you can. Is this rule valid?

- Ask the two learners you are working with to play white together, while you play black and try out both possible options for white to win.
- The positions in the photos shown above (Option A and Option B) are the most interesting positions, because in this position, black loses when capturing.
- To conclude work in the small groups, ask whether there is any remaining way that white could still win provided black plays optimally, and ask them to show it to you. This step is over when all learners are confident the answer is: "No, white cannot win if black plays optimally."

We suggest you demonstrate on the blackboard the two most interesting positions (start with white moving the middle pawn, black capturing, and white being forced to capture with the top pawn (Option A below) or the bottom pawn (Option B) shown above). In both cases, it will lead to black losing if black captures. Use these positions to talk about the overgeneralisation problem (good experience with capturing in the first few moves leads to thinking capturing is always advisable).

Step 2: Human vs human: Reflecting on how we learn

After each player has mastered Hexapawn to such an extent that they are confident they will always win when playing the black pawns, ask learners to discuss in tandem some of the questions below. We suggest you pick out some of these questions depending on your target group. Before writing the questions on the blackboard (or distributing them as a handout) it makes sense to explain to the learners that some questions may seem very easy to answer, with no need for discussion, but they are important because later in the process, you will want to compare the answers of the human vs human phase to the next phase, which will be the learning process of a very simple system that illustrates what goes on inside a computer.

*"**Did you PLAY Hexapawn?"***

"Did you LEARN to play Hexapawn?"

"What was your strategy when deciding on the next move?"

"Did you find yourself imagining you were the other player, like: What will my opponent do next?"

"Did you find yourself thinking in if-clauses: "If I do x, then my opponent will do y or z, and if the opponent does z, then I will do xx"

"Did you make mistakes that led to you losing the game? If so, how did you react to them?"

"Did you master the task of becoming "unbeatable" as the black player?"

"Are you aware that you have become "unbeatable" as the black player?"

"Are you aware of the strategies you used to improve your chances of winning?

"How much fun did you have when playing Hexapawn initially?"

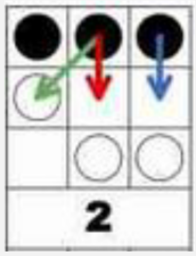
“How much fun do you have when playing Hexapawn now – as a Hexapawn expert when you always win when playing black?”

You can proceed to the next step or choose to discuss the answers that were given to the questions in the plenary.

Step 3. Human vs. randomly playing computer

Now the “computer” is introduced as a mechanical opponent: it makes its moves randomly. You may want to comment this: “Now that the game has become boring for you when you play against each other, let’s reintroduce the fun into the game. I have a chess computer for you that can be your opponent.”

For each game situation there is a small box, labeled with one possible position within the gameplay. Inside the box, different colored beads represent the possible moves. The number on the box indicates which move is carried out. The white player always starts with move one, the computer carries out move two, then the human makes a move (number three), Computer proceeds with move four, and so forth.



If you have a lot of time, it makes sense to build the matchbox computer with your pupils. That means they participate in making the labels on all the boxes. With very little time, you present the ready-made matchbox computer to the pupils. An in-between choice we have often tried out is to at least use the first two boxes as examples of how the computer was built. For this, draw the starting position before the second move (black is about to move) on the blackboard and add the arrows of all possible moves.

To determine which will be the next black move, the computer operator (one of the learners) shakes a box so that one of the beads falls out of it (make a small hole on the side for this), like throwing a dice to determine a move in a board game. The computer operator then carries out the move corresponding to the bead’s color.

From the didactical point of view the version with the matchboxes is the best. But it might be the case that no matchboxes are available. There are two possible alternatives:

Version B

One alternative version of the game uses no boxes but instead a game board and colored cards. The human player – or, with three participants, the game leader – holds the cards up so the computer operator cannot see the colors. The operator then draws one card at random, and the corresponding move is carried out by the operator.

Version C

Another alternative uses dice to decide which move to make. Here the pupils can experience the element of chance in a good way. First the computer operator throws the die and then he or she makes the according move that is indicated in the overview of moves.

There is one special rule: the human, who always plays first with the white pieces, may only open with the middle or the left pawn. This simply reduces the number of possible moves. Because the board is symmetrical, this can be considered an equivalent strategy - it does not change the nature of the game itself. For younger learners (and teachers who are not sure they agree with this explanation), we recommend a matchbox computer with more boxes that represent all possible positions (for example, all three options of left and middle and right pawn in the opening move). Your matchbox computer will then consist of far more than 24 boxes.

At this stage, several rounds are played. Sometimes the computer wins, sometimes the human wins. Whatever happens, at the end of each round the initial setup is restored (= “reset”) by placing all beads inside the box they came from.

If you want to use Hexapawn to practice calculating probabilities, you can already ask pupils to record the frequencies of each player (white or black) winning at this stage rather than starting to do this in step 5 . Black has only one to four options for moves, and the game is always over by the seventh move, so the tree diagram is large but not very complex (see section materials below). In maths lessons on calculating probabilities, you could also ask pupils to calculate (as homework) the overall likelihood of black winning if white plays optimally.

Step 4: Artificial intelligence: The computer makes only the “good moves”

You can now tell the learners:

In step 1, when you played human vs. human, you had all found a strategy for black to consistently win. That was quite clever, but on the other hand, there was no point in playing the game anymore, because it is not much fun if you know who will win from the outset. In step 3, we have reintroduced fun by playing against the matchbox computer. Now chance rules: You sometimes win, you sometimes lose as the “human” (white) player, depending on chance. Ask the pupils:

How could we change the setup of the Matchbox computer in such a way that it would win consistently?

There are two frequent replies:

a.We know which moves are bad moves for black. So we just remove all the beads in the boxes that represent bad moves.

b. We could punish “mistakes”, that means we remove the “losing” bead that led to a loss, so the same mistake cannot be made twice.

If pupils come up with answer b first, you can move to Step 5 and talk about expert systems later, or – if you want to introduce the historically earlier types of AI first - nudge them towards the first answer. Comment that removing all the bad options (“beads”) is a really good idea. But in order to do this, you need to have a human expert in Hexapawn that has already found a way to always win. This expert knowledge could be translated into the setup of the matchbox computer easily: Indeed, the expert simply removes all the beads that represent bad moves that would lead to black losing. This is a quick and simple procedure. Changing the matchbox computer in this way illustrates AI of a certain type: **Expert rules-based AI systems**. That was the dominant type of AI used for decades. It is AI, but it is not yet machine learning. For Hexapawn, to be honest, an expert rules-based AI system would be the fastest and most practical way to get the computer to win.

Step 5: Artificial Intelligence: The computer is punished for “bad moves”

But there may be games where it is far more difficult to find out which move is a good move, maybe near to impossible because there are so many possible positions. That’s why a different strategy for the computer to improve at certain tasks has become increasingly popular. Machine “learning”.

Either learners have already mentioned the idea to reward correct moves or punish mistakes.

If no one comes up with the idea, you can introduce the principle that when the computer encounters a situation in which it has previously lost, it should try not to repeat the same mistake. How could this be achieved?

The solution is to restrict its options after each loss. Specifically, the last move that led to defeat is removed from its possibilities. In the version with boxes, this means taking out the bead of the color that corresponded to the losing move. (In the card version, that colour is crossed out on the move chart.)

In this way, the computer can never make the same mistake twice. Gradually, the computer becomes a “better Hexapawn player” until, after about 12 to 15 rounds, it is nearly unbeatable.

A question for advanced learners: How many rounds of Hexapawn are needed for us to be sure that the computer always wins? If you want to be 100% sure that the computer wins, you must play an infinite number of rounds in this setup: There is always a chance that the "bad move beads" never get picked, so they cannot be eliminated.

After each round, the winner is recorded on a results chart. Over time, it becomes clear that the likelihood of white = human winning decreases step by step. In case of the computer winning the likelihood remains unchanged, in case the computer loses, the elimination of this "losing option" leads to higher chances of winning for the human.

It is also possible to use the tree diagram (see attachments) to demonstrate the pruning of possible options: pupils can cross out the eliminated options and can visualise in the tree diagram how entire branches of possible moves disappear once an early move has been eliminated.

Step 5: Reflecting on how the computer "learns"

At the end, it is useful to encourage pupils to think about what is really meant by "learning" in the case of the Matchbox Hexapawn Computer.

In a tandem discussion and a subsequent plenary discussion address the following questions. They are very similar questions as above in Step 3, but now "you" is replaced by "MHC":

- ***Did MHC (= Matchbox Hexapawn Computer) master the task of winning Hexapawn?***
- *Did MHC PLAY Hexapawn? Should we say "MHC carried out moves" instead?*
- ***Did MHC LEARN to play Hexapawn?** In plenary, discuss different definitions of learning here.*
- ***How much fun did MHC have when "playing" Hexapawn initially?***
- *How much fun does MHC have when playing Hexapawn now?*
- *Is MHC aware that it has become "unbeatable"?*
- ***Is MHC aware of the strategies used to improve its chances of winning?** With future teachers as learners, discuss the role of meta-cognitive learning skills in the plenary.*

More questions and examples to talk about:

- *For example, a child who once discovers that they can look through a glass pane but cannot walk through it will not run into it a second time. By contrast, a fly cannot learn this and continues to fly against the glass.*
- *How does a person deal with situations where rules must be broken?*

  For example: we learn not to touch burning objects because it causes injury. But in fact, a relative of Prof. Dr. Robert Neumann tells a story in family lore of a burning candle falling onto an advent wreath. The wreath was already quite dry and at once caught fire. What would a robot do that had "learned" the rule "do not touch a burning object"? The person in question immediately grabbed the advent wreath and threw it into the sink and let the water run on it. He got burned on his hands but did not hesitate to act — in order to prevent a greater danger. So, you have to know, at what point it might be much better to violate a given rule! For this it is necessary to be able to look at the situation from a meta level (burning your hand in *comparison with the overarching goal of not wanting to die in a burning flat).*

- *Other examples can be discussed where rule-based instructions proved to be wrong. One case: the Warsaw Airbus accident (Lufthansa Flight 2904). One of the problems was: due to aquaplaning, the wheels did not rotate, so the computer did not register that the plane had landed. As a result, the brakes did not come into action until it was too late. More information can be found here:* [*https://en.wikipedia.org/wiki/Lufthansa_Flight_2904*](https://en.wikipedia.org/wiki/Lufthansa_Flight_2904)
- *But do these examples already cover all of human learning? Could we repair these drawbacks of machine "learning" by using a better training dataset that is so extensive that theoretically all rules plus all exceptions to the rules could be "learned"? But practically, what mathematical weight would be given to the harm that would come to different groups of people? How would power imbalance influence who gets to decide on the weight?*

AI unplugged can influence anthropomorphisms and technomorphisms

The AI unplugged HERMMES practice series is aimed at helping learners grasp some of the fundamental ideas underlying machine "learning". At the same time, it can also influence learners' broader conceptions of what it means to be human in the age of AI. When piloting the AI unplugged HERMMES practices in middle and upper school and university (mainly teacher training) courses, AI unplugged courses often led to a reduction in anthropomorphisms. Learners would ascribe less human properties - such as awareness, understanding, learning, playfulness, and so forth - to a computer system when they grasped more of the principles underlying machine "learning". A catchy but oversimplified slogan was uttered by one of the future teachers in a course at Alanus University:

"The more you understand AI, the less you anthropomorphise AI"

Optional Step 6 : Shreksapawn or: Do we learn the same way as the computer?

(recommended in teacher training or with high-school pupils, not for younger pupils):

The "Chinese room" HERMMES Practice (AIU1) addresses questions of differences between human learning and machine "learning" in a more playful, experiential way, and on a different level, so that description and its background section are recommended reading before you go on here.

Micro-phenomenology

As mentioned above, we have observed just such a connection, that learners tend to anthropomorphise AI less after experiences with fundamental ideas underlying rule-based AI and machine "learning" and also tend to technomorphise themselves less (see also Bleckmann, Segessenmann 2023), namely, ascribing less machine-like properties to themselves and their cognitive processes. We are aware that this conclusion does not cover the full complexity of the debate on machine "learning" compared to human learning. We would like to disclose that we are personally glad that this is what many learners conclude after the Hexapawn experience. This gladness is most likely linked to our personal attitudes *as teachers. We perceive ourselves – and the pupils we teach - as unique human beings. We try to encourage them to grasp fundamental ideas without necessarily having to be talented programmers or mathematicians. We are more outspoken in verbalising what happens when computers "learn". But we try to restrain ourselves when it comes to questions of how they learn, and more fundamentally, what they ARE. We do not hesitate to tell them honestly that we perceive them as unique, interesting, and worthy individuals that inspire us with curiosity as to their further biographies. But they may perceive themselves in a different light. So, in the AI unplugged series, we try to ask them questions about what they perceive themselves to be, in the tradition of methods of micro-phenomenology, that can be helpful in investigating a first-person perspective on mental phenomena (Tewes, 2023).*

Embodied cognition

Paula Bleckmann, as a biologist by first training, would also like to disclose here an affinity to the book "In defense of the human being" by Thomas Fuchs, a professor that holds both a medical and a philosophical PhD title (Fuchs 2021). Fuchs puts a lot of focus on embodied cognition, on the idea that humans having a body change what we could call "perception". As opposed to machines, whose input data are zeroes and ones from different input modes (mostly visual, auditory, tactile sensors), human bodies have grown with an interconnection between more than 15 types of sensory receptors, including, at least five different types of receptors in the skin (vibration, pressure, temperature, pain, c-tactile afferences), plus touch, taste, smell, proprioception, vestibular system, and more.

It is simply a mechanical system that is altered by the operator, but it has no awareness.

Considerations of ANT (Actor Network Theory) where the surface of communicative acts in a network of "actors" is investigated, with a focus on the empirical study of the communication systems, without seeing a need to address the questions whether AI can understand the human actor, only investigating whether AI is addressed in a different or similar way to other human actors in the system.

-Same would apply to a person that has fallen in love with their car.

In case you find your own thoughts aligned with this kind of anthropology, you may want to give the learners insight into your own beliefs on the topic. In our experience, this causes a more in-depth thinking process in the learners than if you tried to tell them that you know the TRUTH about the nature of humanity.

"I think of myself as. I perceive you …"

In practice: How to discuss it with future teachers

Watch all of this video or only the end of it:

https://www.youtube.com/watch?v=sw7UAZNgGg8&t=471s (9:36)

Additionally, we suggest you print out the transcript of the passages that can be used to foster debate about differences and similarities between human learning and machine "learning", so the pupils do not have to replay the video too many times when analysing the words in detail:

Transcript:

> *"To improve at hexapawn our matchbox computer actually uses a kind of genetic algorithm. It's a way to solve problems based on natural selection, based on the process that drives biological evolution. The beads of learning in your life may be refined by punishment. Put your hand on a hot stove once and learn that 'Ow! That's painful!' So, you remove the touch-hot-stove bead from your brain. They may also be augmented by rewards: My parents bought me ice cream for getting an A in my exam. Add another get-good-grades bead to your matchbox head computer [...] but by allowing this matchbox computer full of coloured beads to learn, the player who's learning a bit more about learning ... IS YOU."*

Invite teachers to share their experiences when comparing human education and machine "learning":

- *From your experience, also your recent experience with learning to play Hexapawn and the process that led the MHC to win, what would you say are the differences between human development and machine learning?*
- *In your opinion, in which aspects are human learning and machine "learning" similar?*

Invite future teachers to pay attention to the language used in the video:

- *What does the Youtuber mean by "your matchbox head computer"?*
- *Which other scientific terms does he use to support his view that human learning can be equated with machine training processes? Answers to discuss: "genetic algorithm" "natural selection"*

  A genetic algorithm is a computational search technique for finding approximate solutions to optimise models and search problems.

  Natural selection is an evolutionary principle postulated by Darwin. Organisms that are more adapted to their environment are more likely to survive and pass on their genes to the next generation.
- *Do you think the use of these scientific terms will make pupils believe his idea that human learning and machine learning are similar?*
- *Do you think the use of the two examples (reward for good grade, pain as punishment) will make pupils follow his reasoning?*
- *How would you react if a student told you that they had watched the Shreksapawn video? Which questions would you ask?*
- *From what age onward would you watch and discuss the Shreksapawn video with*

your (future) pupils?

Step 7: How to choose and adapt learning scenarios on AI if you intend to avoid anthropomorphisation and technomorphisation

A brief comment on other materials for AI unplugged and CS unplugged. We intend to expand this text in the future. For now, here are some brief notes that describe our thoughts in selecting and adapting teaching resources:

Example 1: Likely to foster anthropomorphisation example: Be the AI (betheai.de) - Here the process in the hidden layers is represented by humans who “translate” text into illustrations and illustrations into text similar to some creative board games where guessing words based on illustrations is the goal of the game. Such creative “party games” require creativity. So when using this practice, inviting pupils to “**Be** the AI”, chances are that they perform this creative act and then come to the conclusion that the processes taking place in machine “learning” are similarly based on creative translations between pictures and words rather than on mathematical processes.

Example 2: We describe a striking contrast between the demystifying intention of Turing Tumble (upperstory.com/en/turingtumble) and the Alia cartoon included in the student booklet in the Turing Tumble package, which contains a questionable cartoon “moment of transcendence” narrative (in detail: Bleckmann, Segessenmann 2025, p. 233-234). Our conclusion is that you can use Turing Tumble, and we have copied a version of the student booklet which contains all the interesting challenges for pupils, but without the Alia cartoon.

Example 3: The Gardner-inspired version of Hexapawn by Seegerer, Lindner (www.aiunplugged.org) was used to compare and improve our version. Thank you to the authors for this great collection. Why did we not stay with the “child-friendly” design? The Seegerer/Lindner version of Hexapawn may seem more child-friendly in the graphic design, instead of white playing against black, monkey plays against crocodile. BUT: Why should a monkey play chess against a crocodile when in fact, neither of these species are known to play chess. And the insinuation is that both players are animals, while in fact one player is a human player (white) in the original lesson plan, and this position is played by a human, and the other (black “player”) is the machine? So sometimes “child-friendly” is not really suitable for children

Example 4: “Brain in a bag” vs. logical network (that is the title of the HERMMES AIU2): Here the name “brain in a bag” is suggestive, insinuating that human thinking works the same way as machine “learning”. This is definitively not applicable for many aspects of embodied cognition (see also elaborations on Shreksapawn and Thomas Fuchs above). The original idea of “neural networks” was indeed inspired by a certain part of the human brain, namely the visual cortex with many layers of neurons and synaptic transmission (namely, the signal transduction is an on-or-off response, it is binary and does not involve non-nervous tissue. See interesting new research on fundamental differences between the interoceptive, more analogue, tissue-based (non-synaptic) transmission (= “feeling”?) and the exteroceptive more digital signal processing (=“thinking”?) (Carvalho, Damasio 2019)). We have therefore changed the name of the practice, the structure of the network, and the signals (from playing cards to simpler shapes), and included the “producing before consuming” HERMMES paradigm in that pupils also are encouraged to make their own logical networks.

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Spieler 1 Mensch
Player 1 Human

Spieler 2 Maschine
Player 2 Machine

Spieler 1 Mensch
Player 1 Human

Spieler 2 Maschine
Player 2 Machine

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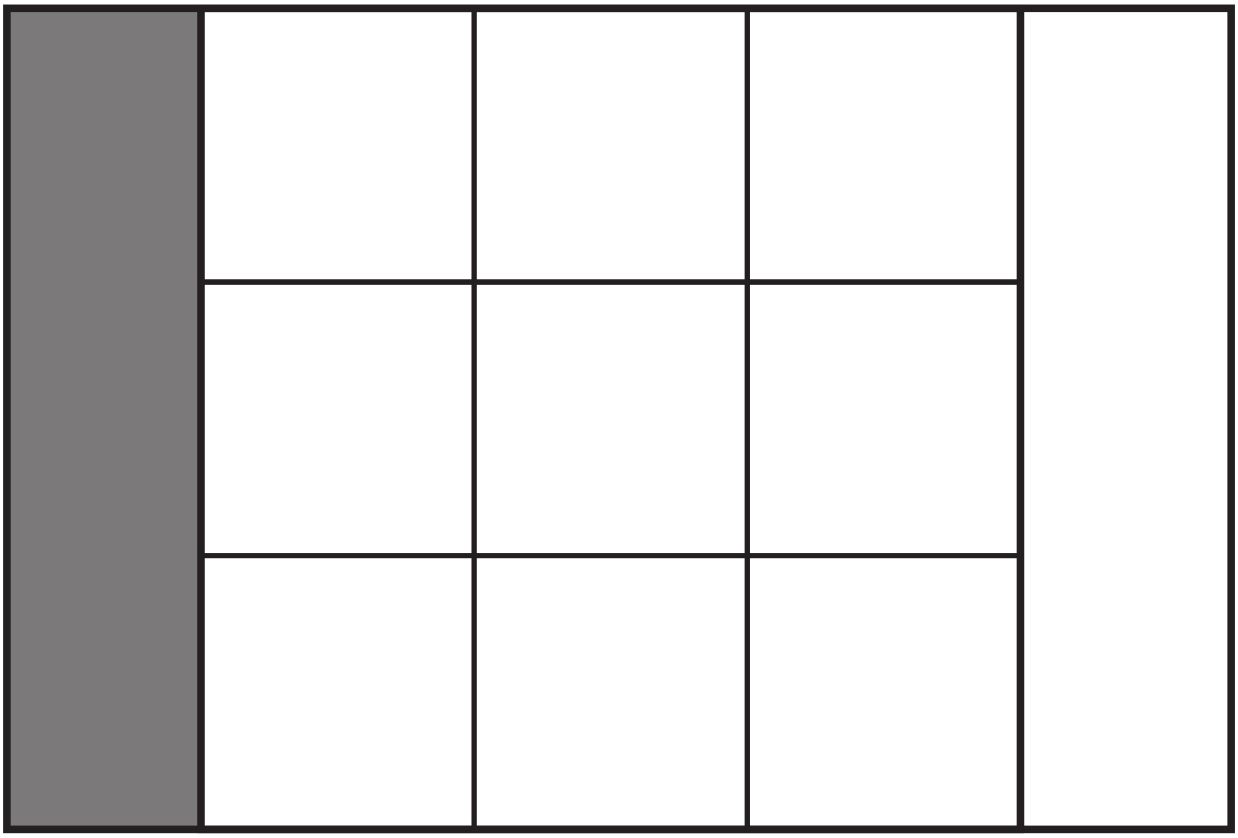
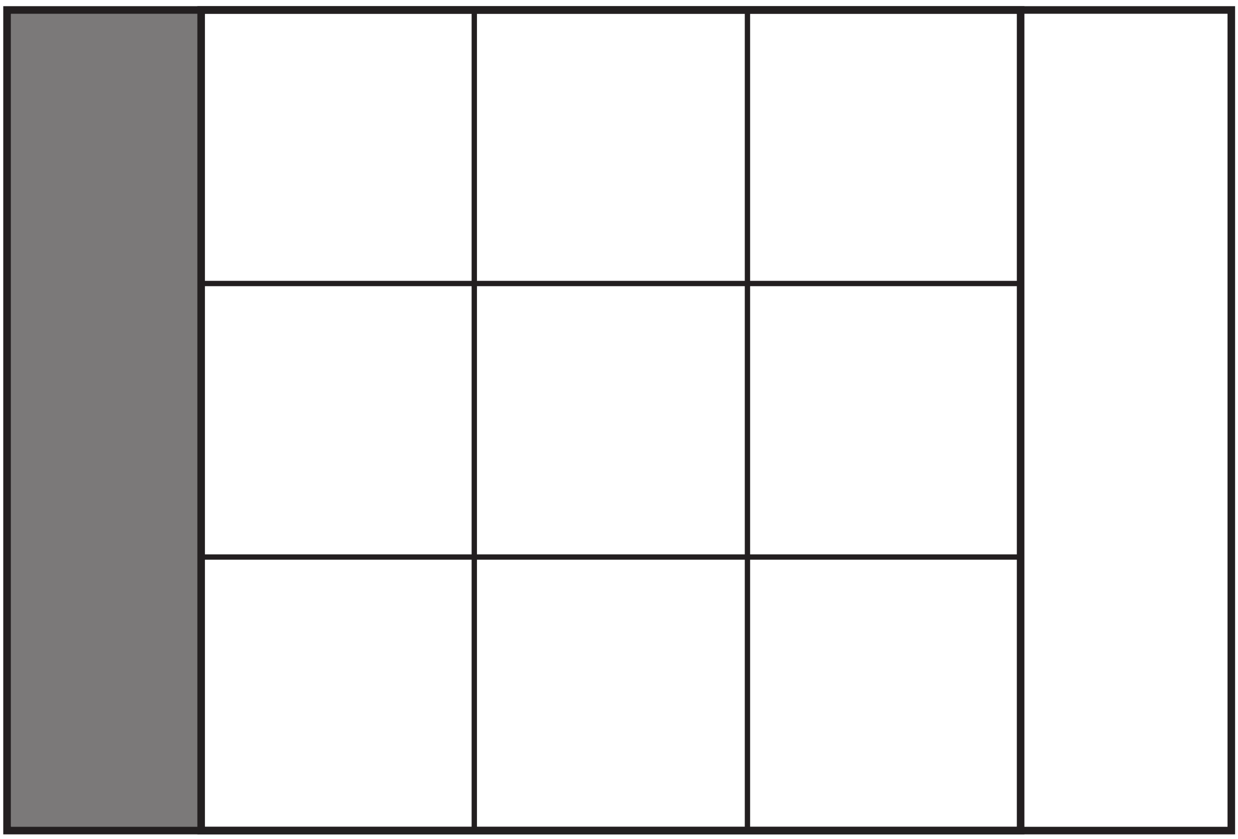
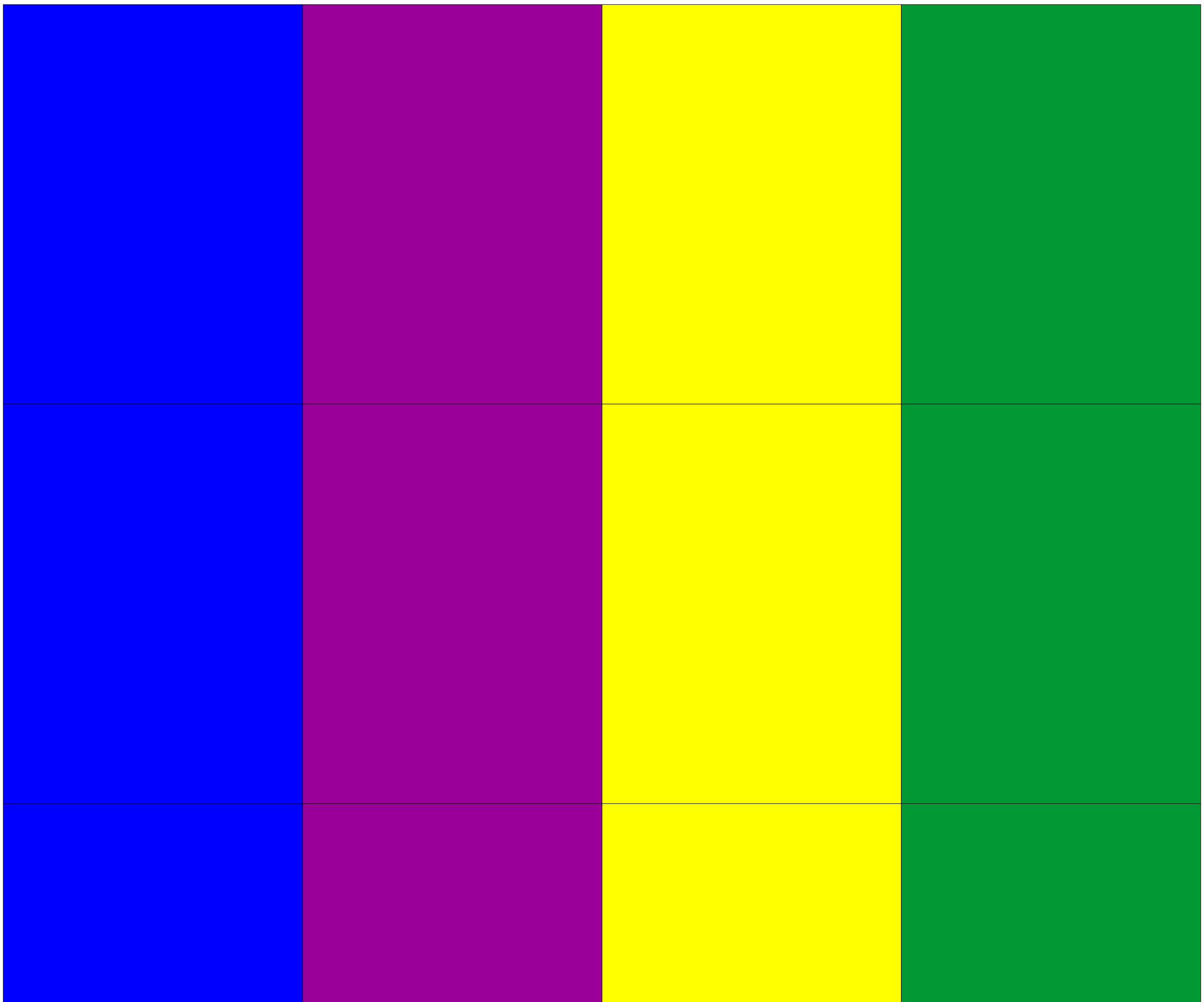
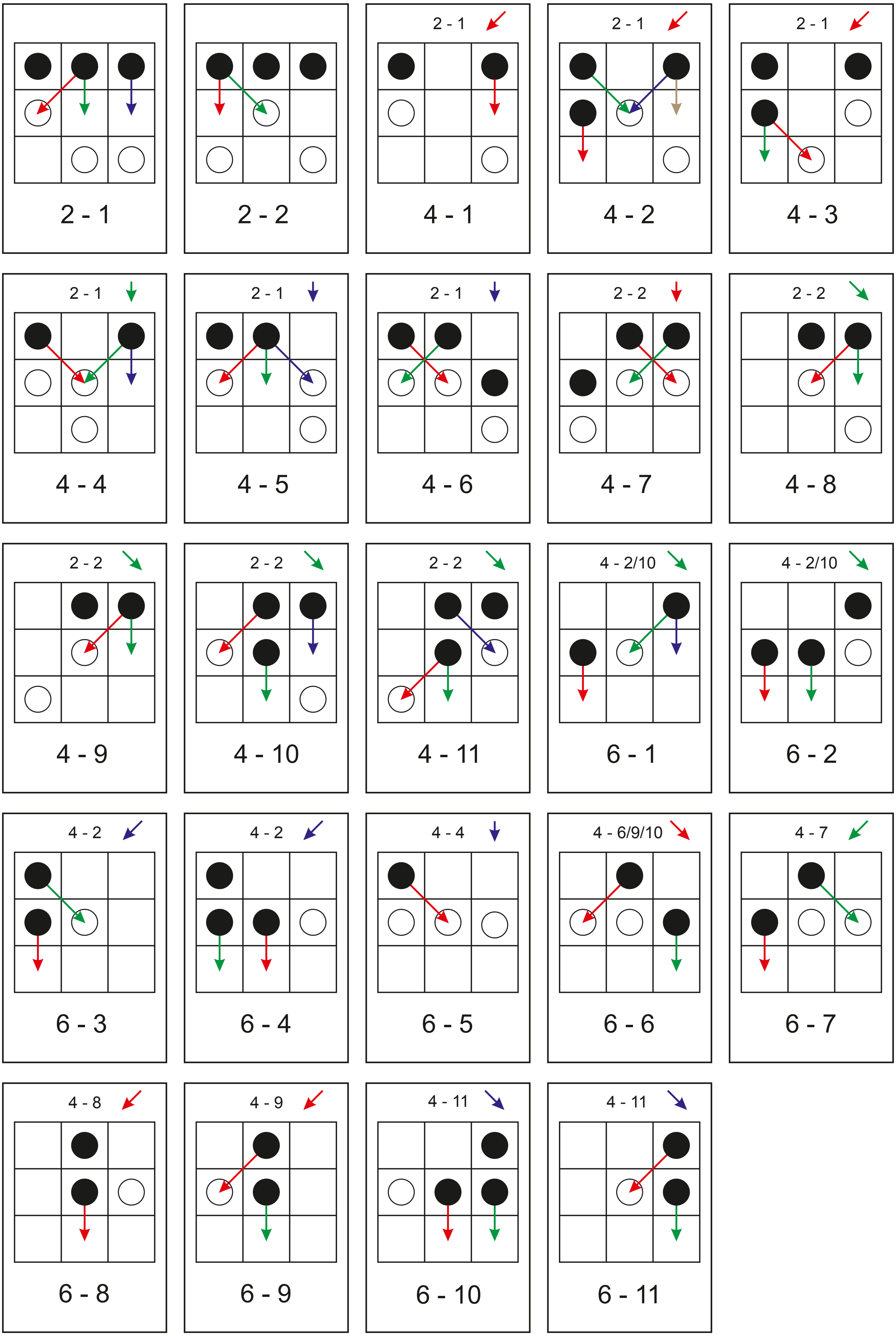


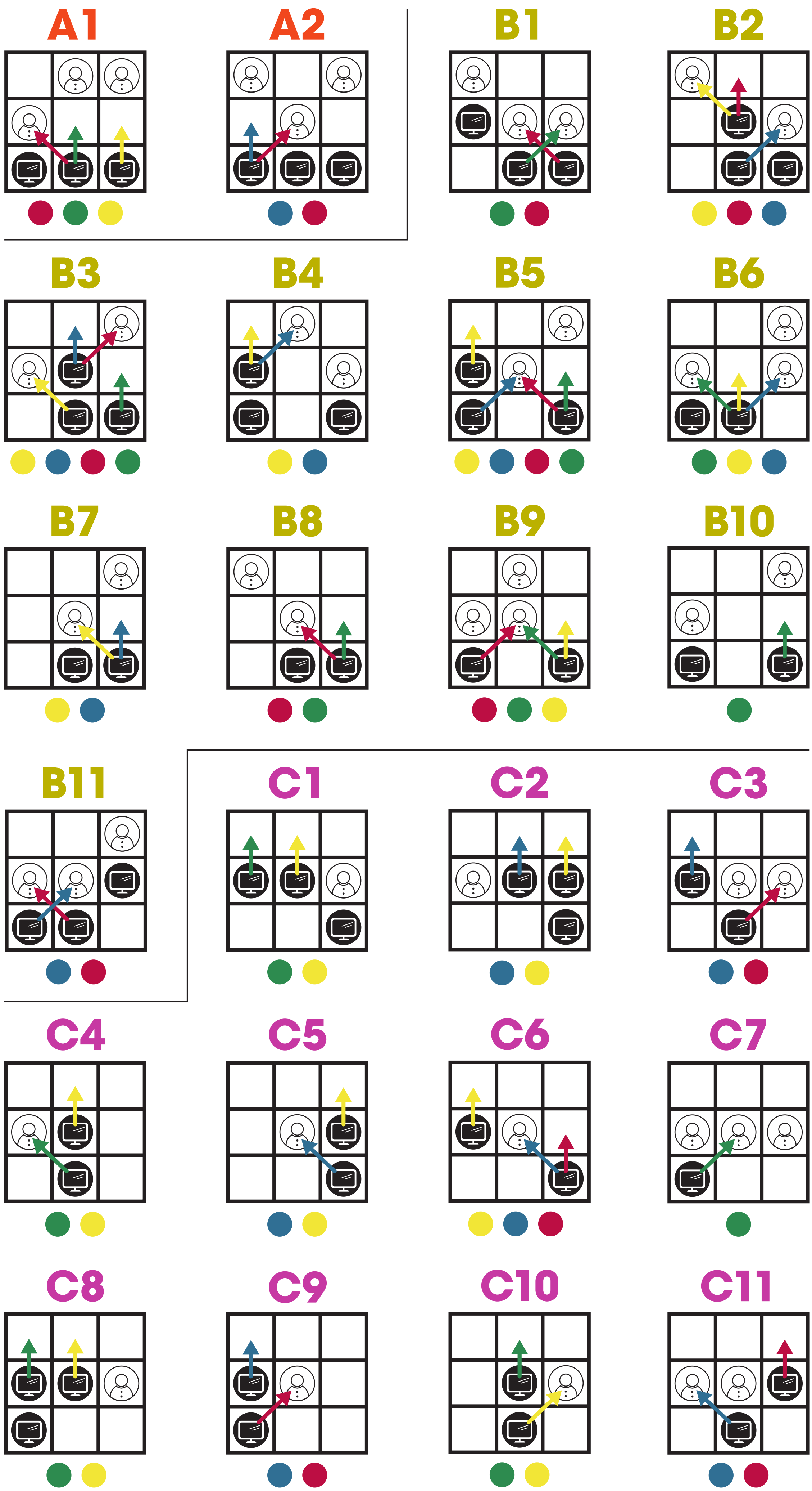




Stickers for use with Matchboxes



Overview of Moves



This document is for use with colored cards to determine the moves of the machine

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Overview of Moves

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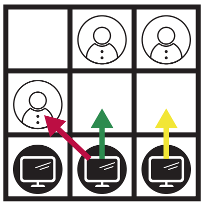
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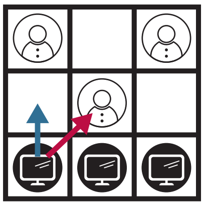
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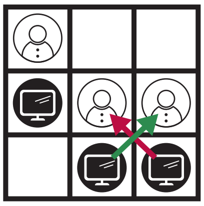
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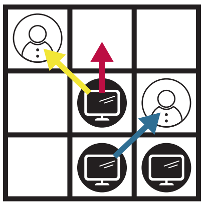
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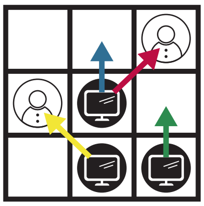
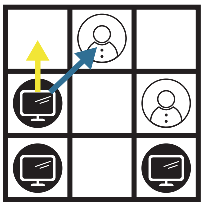

1 2 3 4

B4

1;2;3 4;5;6

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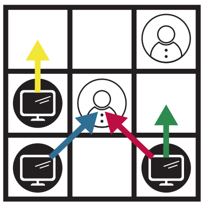
1 2 3 4

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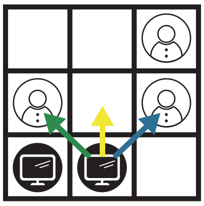
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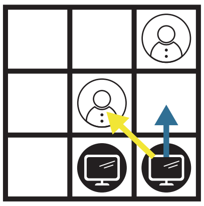
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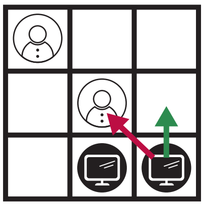
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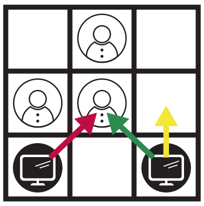
1;2 3;6 5;6

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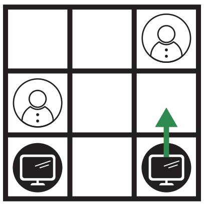
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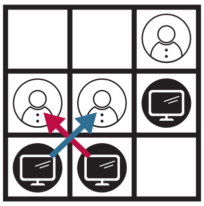
1;2;3 4;5;6

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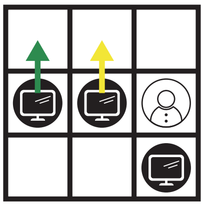
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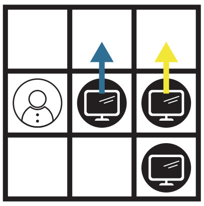
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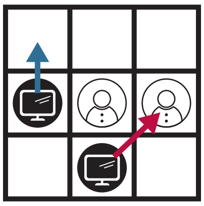
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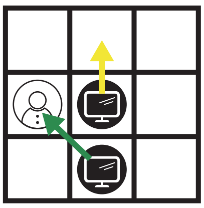
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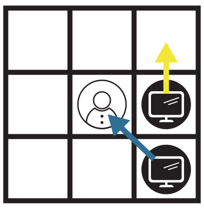
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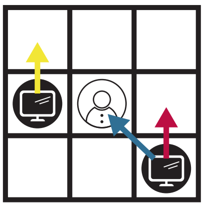
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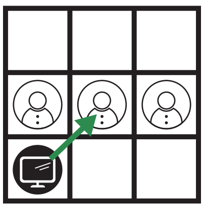
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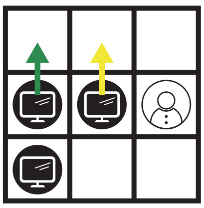
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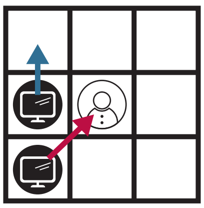
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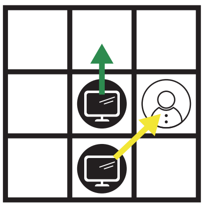
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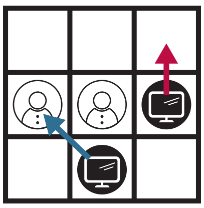
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This document is for use with a die to determine the moves of the machine

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Information Sheet for Human Player

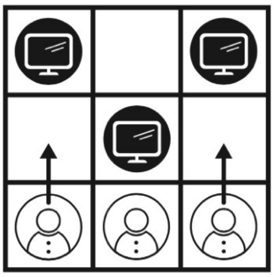
Moves

- The human player has the white pieces and starts with move 1.
- The pieces can only be moved forward.
- An opponent's piece is captured diagonally.
- The game is won when one of your pieces reaches the opponent's side or the opponent can no longer make a move.
- On the first move, either the middle or the right piece must be moved (no restriction due to the symmetry of the game).

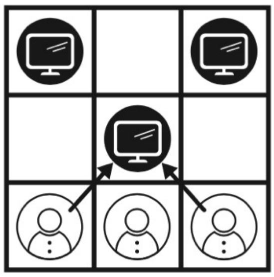
Game progress

- 1st move: Move the middle or right piece
- 2nd move: The machine takes its turn
- 3rd move: The human takes their turn
- ...

How to move?

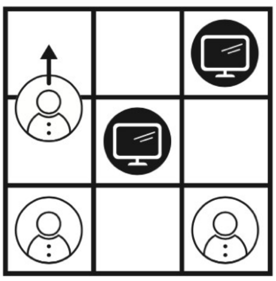


Move straight

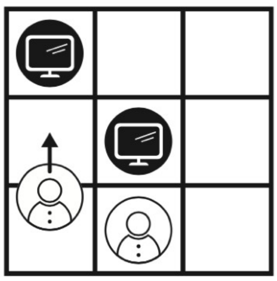


Capture diagonally

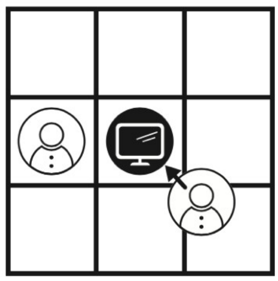
How to win?



Reach opponent’s side



Block opponent



Capture all pieces

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Information Sheet for the Game Supervisor

The game supervisor oversees the game and records the results in the results table at the end of each round.

Moves

- The human player starts with the white game pieces.
- The pieces can only move forward.
- The game is won when a player's piece reaches the opponent's side or when the opponent can no longer make a move.
- An opponent's piece is captured diagonally.
- On the first move, either the middle or the right piece must be moved.

Game progress

- 1st move: The human moves either the middle or the right game piece.
- 2nd move: The machine takes its turn.
- 3rd move: The human takes their turn.
- 4th move: ...

Machine-moves

The game master takes the cards with the available moves for this turn and holds them in a way that prevents the machine operator from seeing the colors. The machine operator draws a card. The move corresponding to the drawn color is then executed accordingly.

At the end of each round

1. The result is recorded in the results table.
2. If the machine has lost:
    - The last move of the machine is crossed out in the overview of moves.
    - (The last move of the machine is crossed out in the move diagram.)

Information Sheet for the Machine-operator

Moves

- The machine has the black game pieces.
- The pieces can only move forward.
- The game is won when a player's piece reaches the opponent's side or when the opponent can no longer make a move.
- An opponent's piece is captured diagonally.

Game progress

Before each move of the machine, the "move overview" is checked to determine the current situation. Then, the available colors for this move are examined.

Machine-moves

The game master takes the cards with the available moves for this turn and holds them in a way that prevents the machine operator from seeing the colors. The machine operator draws a card. The move corresponding to the drawn color is then executed accordingly.

- 1st move: The human player takes their turn.
- 2nd move: The game master selects the colors matching the game situation, the machine operator draws a card, and the move corresponding to the color is executed.
- 3rd move: The human player takes their turn.
- 4th move: ...

At the end of each round

f the machine has *lost*, the *last* color that led to this move is crossed out on the overview of moves" so that this move can no longer be executed if the situation repeats.

Table of Results

turn	human wins	machine wins	Situation and colour taken out (e.g. red possibility crossed out at B8)
1			
2			
3			
4			
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