Reinforcement learning for the manipulation of eye tracking data

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Figure 1: Important and irrelevant information for different classification targets after one iteration.

ABSTRACT
In this paper, we present an approach based on reinforcement learning for eye tracking data manipulation. It is based on two opposing agents, where one tries to classify the data correctly and the second agent looks for patterns in the data, which get manipulated to hide specific information. We show that our approach is successfully applicable to preserve the privacy of a subject. In addition, our approach allows to evaluate the importance of temporal, as well as spatial, information of eye tracking data for specific classification goals. In general, this approach can also be used for stimuli manipulation, making it interesting for gaze guidance. For this purpose, this work provides the theoretical basis, which is why we have also integrated a section on how to apply this method for gaze guidance.

KEYWORDS
Neuronal Networks, Reinforcement Learning, Multi Agents, Differential Privacy, Scan Path, Gaze guidance

CCS CONCEPTS
• Computing methodologies → Multi-agent reinforcement learning; Neural networks; Computer vision;

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1 INTRODUCTION
Due to the spread of the eye tracking technology over many fields and its use in everyday life, the specific information content in the eye tracking signal becomes more and more important [4, 46]. This is mainly due to the fact that the gaze signal is very rich in information and on the other hand that it cannot be turned off or easily controlled by a human [17, 64]. Many applications use this signal, however, still little value is placed on the anonymization of the signal. This is partly due to the fact that the topic of differential privacy has come into the focus of eye tracking research last year [43, 62, 63], but also to the challenge of finding specific patterns in the signal itself that make a person identifiable.

Initially in 2014 the problem of personal information in the eye tracking signal was mentioned for the first time as well as the person specific patterns contained in the signal [41]. They mentioned critical attributes that are contained in the eye tracking data like age, gender, personal preference or health [41]. This information poses
a new challenge to modern eye tracking systems, which must now learn to hide this information. The basic approach of differential privacy is based on adding random noise to the signal: to cover up people specific data. However, this only works in the case of prefabricated features, since modern machine learning techniques such as convolutional neuronal networks are able to adapt their feature extractors. Furthermore, it would be more interesting to find specific patterns either in the stimulus itself or, as in this paper, in the scan path, which we can remove from the signal. On the one hand, this offers an insight into important characteristics which are interesting for science. On the other hand, it can be used in many other areas such as gauze guidance [28, 39] or expertise evaluation [14, 38].

In this paper, we present an approach that is able to learn an image manipulation to hide specific information while preserving other information (Figure 1). Our approach uses reinforcement learning on the sparse representation learned by an autoencoder. This combination allows to manipulate general patterns in an image, since the autoencoder has to reconstruct it based on a reduced set of values. This reduced set can be found in the central part of the autoencoder. It is also called bottleneck, and the following transposed convolutions of the autoencoder reconstruct the image on the basis of this reduced set. Meaning, that those values represent patterns in an image that are manipulated by an agent in our approach. This agent tries to hide specific information by manipulating those values. Another agent tries to train new classifiers to adapt to the manipulated data. This retraining allows our approach to diminish all personal patterns in the data since the classifiers adapt to the manipulated data too.

In the case of gaze guidance, the first step is to learn general patterns about many users. In the case of expert knowledge, this means to find general task specific patterns in the stimulus. Based on this knowledge, a layman can be supported over time by increasing the strength of those patterns in a stimulus image. The expertise level of a person could also be evaluated by the required amplification of those patterns in a stimulus. This was achieved by computing twenty features on movies [9]. This was achieved by computing twenty features on the gaze signal and measuring the difference of these features. For virtual reality head sets, a user authentication was proposed in [68] using different stimuli and analyzing the gaze signal.

However, the high and unique information content in the eye tracking signal only becomes clear when the application for biometrics is considered. Here, it is possible to unambiguously identify the person by means of the eye behavior. The first approaches required a moving point stimulus which was followed by the user [30–32] or static images [45]. In 2010, the first approach that was able to distinguish users with a task independent approach was presented [2]. At the same time, model based approaches that map the gaze behavior on a oculomotor model appeared too [34, 35]. This approach was further developed to distinguish users even if they perform different tasks like browsing, writing, reading, or watching movies [9]. This was achieved by computing twenty features on the gaze signal and measuring the difference of these features. For virtual reality head sets, a user authentication was proposed in [68] using different stimuli and analyzing the gaze signal.

All of these publications show the potential threat to a human by revealing his gaze data. This means also that raw eye tracking data has to be handled with care for storage and for transmission. This topic falls into the field of differential privacy, which has a large theoretical foundation. Practical applications fall into the realm of localization [56], biomedical data [57], and continuous time series

2 RELATED WORK
In this work, we deal with three topics. The first is differential privacy, in which people try to hide specific information. Also other information should remain in the data. To achieve this we use modern machine learning approaches to get a reduced representation of the input images, which ensures that general patterns are manipulated. For this we use deep autoencoders. For the classification, we also use deep nets in combination with the softmax loss function. The manipulation of the data itself is based on statistics and can be understood as Markov process [60]. At the end of this paper we describe a possible application of our approach in the area of gaze guidance. For this reason, we have decided to split the related work into three parts, which are described below.

2.1 Differential privacy
This section contains the range of information contained in eye tracking data, the biometric properties of eye movements, and the general case of differential privacy. In the last part we move on to the modern approaches to differential privacy in eye tracking that appeared last year.

The rich information content available in human eye movements has been shown in several studies. One example is the pupil dilation of a subject. It holds information about the cognitive load [48] as well as the attention to the scene or personal interest in the scene [20]. Mental disorders such as Alzheimer [24], Parkinson [36], or schizophrenia [22] can be detected in the eye movement behavior as well. Additionally, the eye movements hold information about the activity of the human [5, 61], the cognitive state [47] and personal attributes [Hoppe et al. 2018]. While all of this information is already critical, several researchers have shown that the gender and age can be estimated from the eye movements as well [6, 58]. Of course, it is useful for diagnosis or security tasks to be able to extract this information, but this information should not be available to everybody just by receiving your eye tracking data or measuring your gaze behavior.

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All of these publications show the potential threat to a human by revealing his gaze data. This means also that raw eye tracking data has to be handled with care for storage and for transmission. This topic falls into the field of differential privacy, which has a large theoretical foundation. Practical applications fall into the realm of localization [56], biomedical data [57], and continuous time series
signal [10] as it is the case for eye tracking data. The main goal of
differential privacy is to hide the private information while keeping
the utility of the signal as high as possible. Here, utility is the
measure of how good the original signal can be reconstructed. For
the purpose of hiding information, random noise is added to the
signal [12] either to the raw data or in the frequency domain [29, 53].
Adding too much noise to the signal preserves privacy, but makes
the signal itself useless [12]. In general, the utility and privacy
tradeoff is tailored around a specific use case [56], which can be
understood as a classification target in the eye tracking world. For
further information, we refer to survey papers [42, 69].

For differential privacy related to eye tracking data is only cov-
ered by three papers so far. The first publication focuses on head
mounted eye trackers [63]. It proposes a field camera that is able
to avoid the recording of other persons. While this is not directly
related to the research field of differential privacy it falls into the
scope because it considers the problem from another perspective.
The second paper tries to hide information in the eye tracking sig-
nal of the user itself [62]. They use the approach from [8], which
adds random noise to the signal. The third paper is about the pri-
vate information included into heatmaps that are usually used for
visualization [43]. They found that those heatmaps still contain
information about a subject and should therefore be used with
cautions.

### 2.2 Reinforcement learning

Reinforcement learning in the area of machine learning refers to
one or more agents trying to learn a strategy that maximizes their
reward [27, 33]. The agent in this scenario has different actions that
it can perform and after each action it receives a certain reward. For
this, different cases have to be considered. The first case are tempo-
ral actions similar to a walk through a labyrinth where the agent
receives its reward after it tried to go through the labyrinth [27, 33].
This means that after executing several actions, the agent receives
its final reward. In the second case, the agent has several possible
actions without temporal dependency [27, 33]. In the following,
we only deal with the temporally independent application, because
we also pursue this in this work. The scenario of several actions
without temporal dependency can also be understood as a multi-
armed bandit [27, 33]. Here, the agent has the possibility to activate
any number of levers after which it expects a reward. The strategy
to be learned here is the optimal combination, whereby the
consideration of all possible combinations exceeds the computing
capacity of modern computer systems [27, 33]. In the case of the
multi-armed bandit, where each lever has only two states, this
would be $2^{Lever}$. In order to learn this strategy and the optimal
combination of levers, there is exploration on the one hand and
exploitation on the other. In the exploration, the bandit is tested
with new lever combinations regarding the reward, and the learned
strategy is adapted. In case of exploitation, the learned strategy is
used to get the maximum reward. If the exploration does not reveal
possibilities for a greater reward, the process is saturated and the
final strategy is learned [27, 33].

In order to learn complex strategies, there are basically two ap-
proaches; one is model based where a statistical model is given.
This model is formulated as a Markov decision problem and is de-
scribed by states and transitions that are known in advance. For
the training of a model based approach, a multitude of action selec-
tion strategy algorithms have been proposed. The first approach
is called the greedy based approach and usually used together with an
optimistic initialization [27, 33]. Greedy, in this context, means that
the algorithm always chooses the action that maximizes immediate
reward. While this is fundamentally not a bad approach, it does
limit the algorithm to exploring, so a very optimistic initialization
is chosen. This forces the algorithm to look for better and better
solutions because it assumes that they exist. An extension is the
$\epsilon$-greedy algorithm [27, 33]. This algorithm follows the approach
of the common greedy algorithm with the difference that with the
probability $\epsilon$ a random action is chosen. This random selection
ensures exploration at all times. Another approach is called op-
timism in the face of uncertainty. It uses the uncertainty of an
action to estimate its potential and instead of choosing the arm
with the best reward, it chooses the arm with the highest potential
to be the best action [33]. This is due to the problem that each
action has a noisy result and the underlying distribution must first
be determined. Therefore, actions that are taken only a couple of
times have a higher potential based on the already received reward
from this action, in comparison to actions that are chosen often and
the underlying distribution is well known. Uncertainty, in this
context, means that the algorithm is unsure how well it knows the
underlying distribution [33]. The last approach from the model
based approaches is called Upper Confidence Bound (UCB) [33].
This algorithm extends the uncertainty based approach by not only
including the uncertainty of a distribution, but also the estimate
of an upper bound of a possible reward this action has. This is
done by computing confidence intervals over the samples in the
history [33].

The second approach in reinforcement learning is called model
free. Here the algorithm learns a strategies on how to behave un-
der different circumstances. Therefore, the model is not known
in advance, but estimated through exploration. The most famous
approach herefore is called the Q-learning algorithm [44]. This
algorithm learns policies for possibly an infinite amount of states,
whereby each state can have a different amount of actions. It con-
ists of a learning rate and a table that holds the information gath-
ered so far. This table is updated with new observations and new
actions are chosen using the same selection algorithms as described
in the area of the model-based approaches. A disadvantage of the Q-
learning algorithm is that it is only applicable if the state and action
space is small. Therefore, the deep neuronal networks are employed
to replace the table and output the best action by observing the cur-
rent state. This is called the Deep Q-Learning algorithm (DQL) [44].
In contrast to the tables the DQL approach has the disadvantage that
the neuronal networks are nonlinear function approximators that
only receive the reward for training. This means that the network
may not be stable or even diverge [51]. To solve this issue, multiple
approaches have been proposed and combined [44]. The first is
called the experience replay mechanism [44]. For this approach,
the algorithm initializes a replay memory. The initialization is done
using the $\epsilon$-greedy algorithm. Out of this memory, mini batches
are selected and used for training [44]. Afterwards, the neuronal
network is used to make new experiences, which are stored in the
Figure 2: The workflow used for our approach. Agent 1 holds and uses the classifiers and agent 2 the manipulator. Both agents are retrained after a fixed set of steps and have a buffer to hold old and new examples.

memory. Therefore, the network can always learn on old and new experiences and is thus, stable to train [44]. The second approach to stabilize the training of the neuronal network is called fixed target Q-network [44]. For this approach, two neuronal networks are used. The first one is trained based on the memory and, afterwards, used to slowly update the second network after a fixed set of steps of the learning process [44]. This is especially helpful if the initial exploration is not sufficient. Newer extensions for the DQL are Double Deep Q-Learning [65], Deep Q-Learning with Prioritized Experience Replay [59], Dueling Deep Q-Learning [66], Asynchronous Multi-step Deep Q-Learning [50], Distributional Deep Q-learning [3], Deep Q-learning with Noisy Nets [11], and Rainbow Deep Q-learning [21] together with extension in the area of combinatorical approaches of DQL and the Markov decision problem to be able to handle an infinite action space too. For a more detailed overview, we refer the reader to the survey paper [44].

2.3 Gaze guidance

Human vision is a complex process that depends on many factors [26, 67]. A large part of research is currently focused on human gaze prediction [37] and attention [19]. The basic categorization of models in this area can be made into pure stimulus-based attention (bottom-up) [25] and task-based attention (top-down) [26]. Many models have been presented for this purpose, the most important being the Saliency maps [25]. These can be calculated directly based on features in the image [25, 26] but can also be learned task specific by modern machine learning techniques [23, 40, 52]. A large future field of application for attention and gaze prediction is gaze guidance [16, 55]. This is for example needed to train novices in a complex visual task without the presence of an expert. The knowledge and behavior of the experts should be extracted and passed on to the novice as intuitively as possible.

In today’s practice, there are already some techniques which are used [15]. Some of them are color dot [7], subtle gaze direction [1], zoom rectangle [7], zoom circle [7], and spatial blur [18] which are described in the following.

Figure 3: The different gaze guidance approaches used in praxis on a natural scene. From top left to bottom right no modification (A), color dot (B), zoom rectangle (C), zoom circle (D), and spatial blur (E).

Figure 3 shows the different approaches together with the unmodified scene (A). The color dot approach in Figure 3 (B) is shown for a duration of 120 ms. Afterwards, it is turned off and activated again after 2 seconds. For the subtle gaze direction approach (Figure 3 (C)) the brightness is alternately increased and reduced in a fixed area. Zooming rectangle and zooming circle rescale the area surrounding the wanted gaze position and overlay it on the image as shown in Figure 3 (D,E). The last approach is spatial blur. The entire image is blurred using a Gaussian filter with the exception of the target region.

As can be seen in Figure 3, these are effective approaches. However, all five approaches have the disadvantage that the manipulation of the image is conspicuous. This makes it impossible to subconsciously train visual behavior where we see the potential advantage of our approach. It must also be said that in the area of gaze guidance, we only present the theoretical implementation and
cannot prove this advantage experimentally. However, we see this as a very promising area for further research.

3 METHOD

Figure 2 shows the general workflow of our approach. The autoencoder is trained preliminary to reconstruct the image. In its central part, it holds values that correspond to general patterns for the reconstruction of the image (Bottleneck in Figure 2). The idea behind using the autoencoder is that it reduces the input data \( (64 \times 64 \times 3 = 12.228 \text{ zu } 4 \times 4 \times 256 = 4096) \) and thus also the possible action combinations of Agent 2. Furthermore, it ensures that in the end, an image is still generated that is similar to the input image or consists of general patterns compared to a direct manipulation of the image by Agent 2. Agent 2 is the reinforcement part of our approach. It learns a manipulation of the bottleneck from the autoencoder based on previous seen input images and the classification result from Agent 1. This classification result is only the difference between the good (Green classifiers in Figure 2) and bad (Red classifiers in Figure 2) information revealed by the classifiers. This difference is used as reward in agent 2 for the performed manipulation, whereas the image itself is the state. The different classification objectives (Document type, expertise, subject, gender) in Figure 2 are intended to indicate that our approach supports any number of classifiers. Agent 2 tries to worsen the accuracy of the red classifiers and to keep the accuracy of the green classifiers high. In contrast to this, agent 1 tries to adapt the classifiers to the new image manipulation by retraining them. In the following each part is described in detail.

Figure 4: The used neuronal network architectures for the autoencoder.

Figure 4 shows the architecture of the used autoencoder. Each convolution block is followed by a rectifier linear unit (ReLU) and max pooling for size reduction. For the decoder of the autoencoder, we used transposed convolutions instead of pooling. The input to the network is an image with size \( 64 \times 64 \times 3 \). The bottleneck in the autoencoder is the block with size \( 4 \times 4 \times 256 \). For the training, we used stochastic gradient descent with an initial learning rate of \( 10^{-2} \) decreasing each 200 epochs by a factor of \( 10^{-1} \). The training stops at a learning rate of \( 10^{-7} \). Weight decay was set to \( 5 \times 10^{-4} \) and momentum to \( 9 \times 10^{-1} \). During training, we used a batch size of 40 and the L2 loss formulation. This autoencoder is trained only once before starting our reinforcement learning approach.

The classifiers used in agent 1 (Figure 2) use a similar structure as the autoencoder. A detailed view of the classifiers can be seen in Figure 5. Each convolution block uses a ReLu together with a max pooling operation. Before the first fully connected layer, we used a dropout, which deactivates 50% randomly. A and B in Figure 5 have the same structure except for the last fully connected layer, which has either eight (Subject) or four (Stimulus image) output neurons. For the training, we used stochastic gradient descent with an initial learning rate of \( 10^{-4} \) decreasing each 500 epochs by a factor of \( 10^{-1} \). The training stops at a learning rate of \( 10^{-7} \). Weight decay was set to \( 5 \times 10^{-4} \) and momentum to \( 9 \times 10^{-1} \). During training, we used a batch size of 50 and the log multi class loss with softmax.

Since these classifiers are subject to the cyclic training of agent 1, they are always re-trained once the reinforcement learning has stabilized. This new training is done with a random initialization. The idea behind this is that the convolutions, which learn new feature extractors, adapt to the new image manipulation and thus improve the classification result. The training itself is done using the not manipulated and all the manipulated images seen so far (only from the training set).

Figure 6: Used setup of Agent 1 with a memory for manipulated data seen in the past.

Figure 6 shows the workflow for agent 1 with the memory. In comparison to Figure 2, which is a general overview, it can be seen that we now have only two classes. Those two classes are also used in our experiment for the evaluation section which is
In the memory (Figure 6) are all the seen manipulated images from the training set together with their labels. Images from the validation set are discarded and therefore, not stored in the memory of agent 1. For the training and test set, we made a 50% to 50% split. We separated the data to produce equal amounts of stimulus and subject classes. As can be seen in this description, agent 1 does not use reinforcement learning. This agent can be understood as a supervised learner, which retrains its classifiers.

Figure 7: The used architecture of the Deep Q-Learning algorithm (DQL) in agent 2.

In contrast to agent 1, agent 2 uses reinforcement learning for training. The used DQL model can be seen in Figure 7. It consists of three convolution blocks and a fully connected output layer. The input of this model is the current image, which is called the state and the output of this model (1024 fully connected neurons) are the actions. Between each convolution block, we used ReLu and max pooling as in the models before. The output of the last layer was set if it was greater or equal to 0.5, otherwise it was set to 0. Meaning, our model could either deactivate a feature in the bottleneck of the autoencoder or let it unchanged. For the training we used stochastic gradient decent with a fixed learning rate of $10^{-4}$. The training stops after ten epochs of training on the entire memory of agent 2. Weight decay was set to $1 \times 10^{-5}$ and momentum to $9 \times 10^{-1}$. During training, we used a batch size of 100 and the L2 loss formulation for reinforcement learning ($\text{predicted} - \text{actual}$)$^2$. The parameter predicted in this context means the result of DQL1 from the current input image. Since there is no ground truth in reinforcement learning, the parameter actual is computed based on a second network (DQL2) and the reward $R$. Therefore, the ground truth is formulated as $\text{actual} = R + y \cdot \text{DQL}2$. As mentioned before, $R$ is the reward (Result of agent 1), DQL2 is the output of a second network and $y$ is the discount factor, which is adjusted through training so that the net explores more in the beginning. This usage of two neuronal networks is called fixed target Q-network [44]. Therefore, after ten training runs of DQL1, we set $\text{DQL2} = \text{DQL1}$ since DQL1 has stabilized.

In addition to the fixed target network, we use the experience replay mechanism [44] as can be seen in Figure 8. As mentioned in the related work, this concept describes the memory which holds all examples (Stimulus, actions, and classification result). In this memory, we only store examples from the training set, since we want to evaluate our approach especially for unseen data. This memory is initialized before starting the entire approach and the networks DQL1 and DQL2 are trained on it. For this initialization, we compute the change of each value in the bottleneck of the classification and store it in the memory of agent 2. In addition, we compute one hundred random changes of 2-100 values in the bottleneck. This means that for the change of two values, we compute one hundred random changes and the same for three values, four values, and so on.

For data augmentation of all models, we used random noise which was in the range of 0-20%, cropping and shifting the scanpath. Cropping in this context means that we extracted randomly 60-100% of the scanpath and draw it on the input image. With shifting, we mean a randomly selected constant shift of the entire scanpath. This shift was selected in the range of 0-30% of the stimulus size.

4 EVALUATION

For our experiments, we used the data provided with the ETRA 2019 challenge [49, 54]. In this data, 8 subjects with 120 trials per subject are recorded. Therefore, it consists of 960 trials with a length of 45 seconds per trial. They recorded four different tasks namely visual fixation, visual search, and visual exploration. Additionally, four different stimuli were presented; Which are blank, natural, where is waldo, and picture puzzle. For the image generation out of the raw gaze data files, we used the approach from [13]. This means that the raw gaze data is in the red channel as dots, the blue channel holds the time by adjusting the intensity of the dot, and the green channel holds the relation ship of the gaze points by connecting them as lines.
We conducted two experiments. The first experiment shows the results of our approach for different iterations, as well as before and after the adaption of the classifiers (agent 1). This experiment shows that our approach is capable of removing unwanted information in the scanpath. In this scenario, it is the information of the subject.

In the second experiment, we evaluate the importance of different channels of the input image for different iterations of our approach. This experiment shows the advantage of our approach to other differential privacy methods since the feature extractors (Neuronal networks in agent 1) adapt to the new image manipulation as well as our image manipulation technique. For all experiments, we used a 50% split of the data where the test and validation set contain always equal amounts of subjects and stimuli samples.

### Table 1: Accuracy of the classifiers after each iteration and before as well as after the adaption of agent 1.

| Iteration | Before Adaption | After Adaption |
|-----------|-----------------|----------------|
|           | Stimulus | Subject | Stimulus | Subject |
| Initial   | -       | -       | 0.96     | 0.93     |
| 1         | 0.95    | 0.13    | 0.96     | 0.93     |
| 2         | 0.95    | 0.11    | 0.95     | 0.91     |
| 5         | 0.91    | 0.12    | 0.93     | 0.52     |
| 10        | 0.88    | 0.14    | 0.91     | 0.31     |
| 15        | 0.78    | 0.12    | 0.86     | 0.22     |
| 20        | 0.81    | 0.13    | 0.83     | 0.15     |
| Chance level | 0.25 | 0.12 | 0.25 | 0.12 |

Table 1 shows the classification results per iteration. With iteration we mean that the reinforcement learning (agent 2) has stabilized, which are approximately one thousand training runs. After each iteration, agent 1 starts to retrain the classifiers, which is indicated by the adaption rows. The first line in Table 1 shows the initial results of the pretrained classifiers. At the bottom of Table 1, the chance level is shown. As can be seen agent 2 always succeeds in dropping the classification accuracy for the subject close to the chance level. Afterwards, agent 1 adapts the classifiers, but with less success for the subject classification if the process over all iterations is considered. In the last iteration (20), the training of the subject classifier fails and is close to the chance level.

### Table 2: Importance of spatial (R, G; red and green channel) and temporal (B; intensity in blue channel) features for the classification per iteration. The importance is measured in percent of values changed in total per channel.

| Iteration | Red (Spatial) | Green (Spatial) | Blue (Temporal) |
|-----------|---------------|-----------------|----------------|
| 1         | 72%           | 12%             | 16%            |
| 2         | 19%           | 69%             | 12%            |
| 5         | 36%           | 31%             | 33%            |
| 10        | 41%           | 39%             | 20%            |
| 15        | 38%           | 40%             | 22%            |
| 20        | 37%           | 35%             | 28%            |

Table 2 shows the percentage amount of changed values per channel (\( \frac{\text{Changed-\text{values-channel}}}{\text{Changed-\text{values-all-channels}}} \times 100 \)). Due to the construction of the image with raw dots in the red channel, connected dots in the green channel, and the time as intensity value per dot in the blue channel, we can estimate the importance of their contribution. For iteration one, it can be seen that the subject information was mainly extracted out of the red channel, which holds only spatial information. In the second iteration, this swaps to the green channel, which holds the interconnections between the gaze points and therefore the spatial information. After five iterations, the amount of changes has balanced per channel. If we compare this result to Table 1, it can be seen that this already had a significant impact on the adaption of the subject classifier. After the last iteration, the amount of changes has again nearly balanced, where the blue channel is the lowest. Since the blue channel is the only channel that has temporal information, it could be argued that it is less important for the subject information since the blue channel also contains spatial information. This statement is of course purely hypothetical and requires further experiments and research as well as another construction of input data.

### 5 LIMITATIONS

In general it has to be mentioned that reinforcement learning using deep neuronal networks can be very instable. One problem of our approach is the adjustment of \( y \), which is the discount especially at the beginning. In addition, the random initialization of the DQL network can be treacherous since the approach can fail in the beginning just because of the random initialization. These problems are of course generally known in the field of reinforcement learning and should only serve as an indication for other researchers who would also like to enter this field. In addition, the usage of the memory requires a large amount of space, which has to be stored on the hard drive. Therefore, it is advisable to use flash memory.

### 6 APPLICABILITY TO GAZE GUIDANCE

Figure 9 shows our idea for the usage of gaze guidance. In this figure, agent 2 is the image manipulator, which should learn how to manipulate the image to receive the highest reward. Therefore, agent 1 makes a regression for the knowledge level. Since most of the current research focuses on the classification between experts and novices, this information can also not be obtained easily. Our idea to make a regression out of the classification data is the distance of the outcome to the class of experts. For neuronal networks, this would mean the distance to 1 in this binary classification task (-1 novice and 1 expert). For other machine learning methods, like \( k \) nearest neighbors, the distance could be obtained by the distance to the expert cluster; and similar for support vector machines, by using the distance to the hyperplane and beyond into the class of the experts. The pretraining of the approach could be done using existing data. The regressor in agent 1 could be trained using supervised learning. For agent 2 the initial subset of a scanpath would be set by a randomly selected expert eye tracking data file. Afterwards, the difference of the manipulated stimulus has to be computed. The distance of this difference (Heatmap convolved with a Gaussian) could be used as reward function. This is only for pretraining and could only help to stabilize the neuronal network.
for the real learning task. Afterwards, users would need to train the neuronal network in agent 2 online. We assume that this will require a more extensive study. The advantage of this, however, is that one would receive a training system for specific tasks, which can be used cost-effectively. In addition, the final results of the guidance could help in understanding gaze guidance itself better. This means that it is so far still unclear if we need to highlight the final location or the path to the location as well as their no answer what regarding the optimal highlighting method.

7 CONCLUSION

In this work, we showed the applicability of reinforcement learning for differential privacy. It was shown that it can be used successfully for hiding specific information in eye tracking data. In addition, it can be used to evaluate the features and is able to adapt to an adaptive attacker (Agent 1 in Figure 2). Our approach is theoretically also capable of removing as well as perserving the information of multiple classification targets. We also inspected the application area of gaze guidance for this approach, where ground truth information is difficult to obtain due to the individuality of humans. Further research will go into this direction especially for novice training based on fixed stimulus manipulation. In contrast to the obvious image manipulations as shown in Figure 3, we hope that our approach leads to an non-obvious guidance of novices and therefore, improves the training quality and economic efficiency.

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