

Adversarial Attacks on Classifiers for Eye-based User Modelling

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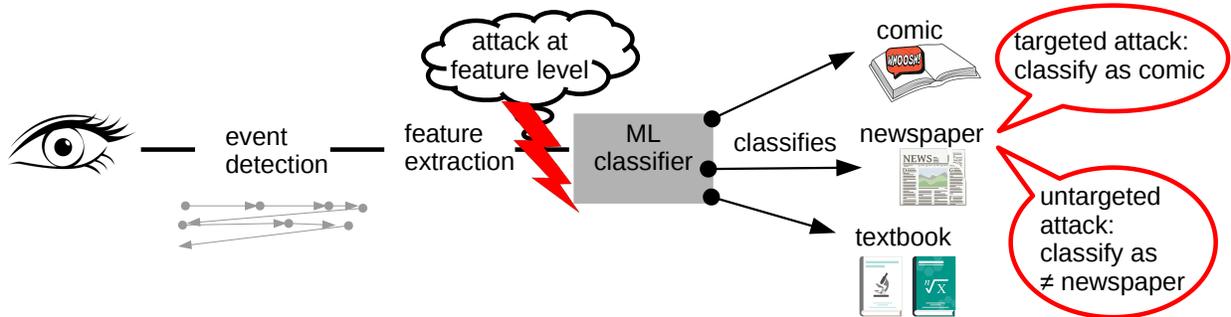


Figure 1: We study adversarial attacks on classifiers for eye-based user modelling at the level of raw gaze data and after feature extraction, with and without targeting a specific class, as well as with and without knowledge about the internal classifier gradients. We do so on the sample task of document type classification from eye movements during reading.

ABSTRACT

An ever-growing body of work has demonstrated the rich information content available in eye movements for user modelling, e.g. for predicting users' activities, cognitive processes, or even personality traits. We show that state-of-the-art classifiers for eye-based user modelling are highly vulnerable to *adversarial examples*: small artificial perturbations in gaze input that can dramatically change a classifier's predictions. We generate these adversarial examples using the Fast Gradient Sign Method (FGSM) that linearises the gradient to find suitable perturbations. On the sample task of eye-based document type recognition we study the success of different adversarial attack scenarios: with and without knowledge about classifier gradients (white-box vs. black-box) as well as with and without targeting the attack to a specific class. In addition, we demonstrate the feasibility of defending against adversarial attacks by adding adversarial examples to a classifier's training data.

CCS CONCEPTS

• Security and privacy → Human and societal aspects of security and privacy.

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1 INTRODUCTION

In recent years, advances in mobile eye tracking [Kassner et al. 2014; Tonsen et al. 2017] as well as learning-based gaze estimation and eye contact detection using off-the-shelf cameras [Zhang et al. 2017, 2019] have spurred research on eye-based user modelling. That is, the use of machine learning to predict various (potentially previously hidden) user characteristics from eye movements, such as users' activities [Bulling et al. 2010], cognitive processes and states [Bulling and Zander 2014a; Sattar et al. 2015], or even personality traits [Hoppe et al. 2018]. Combined with the continuing integration of eye tracking into head-mounted virtual and augmented reality headsets, eye-based user modelling promises a range of exciting new applications that may already become possible in the near future, such as mental health monitoring [Vidal et al. 2012a] or life logging and quantified self [Kunze et al. 2013a, 2015].

However, with ever-more widespread integration and thus availability of gaze data comes an ever-increasing risk of misuse and attacks on users' privacy. Examples for potential adversaries are headset manufacturers trying to obtain personal information about consumer interests or preferences, malicious applications running on the host computer to which the headset is connected that spy on users' activities, or third parties trying to exploit eye gaze data

that is available publicly or that has been obtained in a targeted attack. Despite all of these diverse threats, research has so far mainly focused on ocular biometrics [Nigam et al. 2015] or secure user authentication using eye movements [Holland and Komogortsev 2011]. Researchers have only recently started to study some of these threats and proposed first solutions to making eye tracking privacy-aware – both at the hardware [Steil et al. 2019b] and software [John et al. 2019; Liu et al. 2019; Steil et al. 2019a] level.

This work contributes another building block to this emerging research field of *privacy-aware eye tracking* by studying, for the first time, adversarial attacks. That is, the process of creating small artificial perturbations in gaze data input, better known as *adversarial examples*, that, if fed to a classifier, can dramatically change the classifier’s predictions. Adversarial examples and attacks have only fairly recently started to be studied in the intersecting research field of computer vision and security [Papernot et al. 2018] but have not yet received any attention in the eye tracking community. We study adversarial attacks on classifiers for eye-based user modelling for the sample task of document type recognition from eye movements during reading [Kunze et al. 2013b]. We picked this task given that reading is a truly pervasive activity, widely studied in different fields including eye tracking research, and has been the subject of a recent study on using differential privacy for privacy-aware eye tracking [Steil et al. 2019a].

We study the feasibility and performance of this attack in different scenarios that we carefully chose to represent real-world use cases (see Figure 1): Attacks with and without knowledge about the internal classifier gradients (white-box vs. black-box) as well as with and without targeting the attack to a specific class. To create adversarial examples that are suitable to attack classifiers for eye-based user modelling in the white-box model, we use a recent gradient-based method – the Fast Gradient Sign Method (FGSM) [Goodfellow et al. 2014]. In a nutshell, FGSM computes the classifier’s gradient and iteratively perturbs a particular sample until it crosses the class decision boundary and is misclassified (see Figure 2). For the black-box attack model, where no gradients are available, we propose a simple method that randomly perturbs single data points in the stream of raw gaze data such that the sample is misclassified.

The specific contributions of our work are three-fold. 1) We are the first to study the vulnerability of state-of-the-art classifiers for eye-based user modelling to adversarial attacks. 2) We conduct comprehensive evaluations that provide detailed insights into different adversarial attack scenarios representing real-world use cases. Furthermore, we explore the feasibility of defending against adversarial attacks by using the same gradient-based method to generate adversarial training data. 3) We discuss the obtained findings and derive a set of recommendations for researchers and practitioners working on eye-based user modelling.

2 RELATED WORK

Our research is related to previous works on 1) predicting user characteristics from eye movements, 2) privacy-aware eye tracking, and 3) the creation and use of adversarial examples.

2.1 Predicting User Characteristics from Eye Movements

Eye-based user modelling, i.e. the computational task of predicting diverse user characteristics and general user context from eye movements [Bulling et al. 2011], has gained significant attention in recent years. The field was pioneered by Bulling et al. [Bulling et al. 2012, 2010] who demonstrated that different office activities, including reading, could be robustly detected from eye movements alone in both stationary and mobile settings. They also introduced a large set of new eye movements features that cover the main eye movement types (saccades, fixations, and blinks) and that we use in this work for document type classification from eye movements during reading. As such also closely related is the work by Kunze et al. [Kunze et al. 2013b] who showed that the type of document being read could be predicted from eye movement data. In later work, Bulling et al. [Bulling et al. 2013] and Steil et al. [Steil and Bulling 2015] demonstrated that high-level contextual cues – e.g. social interactions, focused work or whether a person was inside or outside – could be extracted from day-long recordings of eye movements in both a supervised and unsupervised fashion.

In addition to different activities, the eyes are also a rich source of information on human cognition and user characteristics difficult or impossible to assess using other modalities [Bulling and Zander 2014b]. Early work by Hess et al. [Hess and Polt 1960] showed that a person’s interests are reflected in eye movements, while Matthews et al. demonstrated that the eyes also reveal users’ cognitive load [Matthews et al. 1991]. Eye movements can also differ for women and men, e.g. when looking at faces [Sammaknejad et al. 2017]. More recent work has demonstrated that visual search intents, i.e. targets of visual search, can be robustly inferred [Jang et al. 2014; Sattar et al. 2017a, 2015; Zelinsky et al. 2013] and even visually decoded similar to a photo-fix [Sattar et al. 2017b] by combining information on users’ eye movements and the underlying image. Recent work has even shown that eye tracking data collected during everyday activities allows to infer personality traits [Hoppe et al. 2018]. Finally, eye movements are linked to a range of potentially highly sensitive mental health issues [Vidal et al. 2012a], such as Parkinson’s [Kuechenmeister et al. 1977] or schizophrenia [Holzman et al. 1974].

All of these works demonstrate that rich but also highly sensitive personal information about who we are, what we do, and how we think can be inferred from eye movements. At the same time, people typically do not consciously control their eyes and are, as such, unaware of what they reveal [Steil et al. 2019a]. Taken together, these observations point at the significant risks and therefore also at the urgent need to not only better understand possible attack vectors on methods for eye-based user modelling, including the classifiers themselves, but also to develop methods to protect from these attacks. Adversarial attacks, one of these key attack vectors, has never been studied in the context of eye tracking before.

2.2 Privacy-aware Eye Tracking

Privacy and security has only recently started to be investigated in eye tracking research. Liebling et al. [Liebling and Preibusch 2014] were the first to summarize which private information can be extracted from the eyes and discussed several approaches for

how to protect privacy. One of these ideas was implemented by Steil et al. [Steil et al. 2019b] who developed a physical shutter for the scene camera of mobile eye trackers. The system detected privacy-sensitive situations, automatically closed the shutter and re-opened it when eye movement analysis showed that the user moved out of the privacy-sensitive situation or activity. Another approach to preserve privacy is the application of noise. While Steil et al. [Steil et al. 2019a] applied noise at the feature level using a differential privacy method and showed that gender and identity could be protected while utility for document type classification could be preserved, Liu et al. [Liu et al. 2019] noised aggregated gaze heat maps. Our work adds a novel attack vector to the emerging field of privacy-aware eye tracking by, for the first time, attacking the classifier instead of the data.

2.3 Adversarial Examples

Research on adversarial examples started with pioneering work by Lowd and Meek [Lowd and Meek 2005] and Dalvi et al. [Dalvi et al. 2004]. With the rise of neural networks, the issue of adversarial examples has started to receive a lot of additional attention. We refer the reader to Papernot et al. [Papernot et al. 2018] for an extensive overview of the current state of the art.

We focus in our work on test time attacks, i.e., the attacker does not manipulate the training process but aims to change classifications at test time. In this setting, researchers generally distinguish between white-box and black-box attacks. For white-box attacks, the trained classifier and all its components are available to the attacker, most importantly allowing her to compute the classifier’s gradients. These are used in gradient-based attacks, such as the Fast Gradient Sign Method (FGSM) [Goodfellow et al. 2014] that we also use in this work. The currently best performing attack was developed by Carlini and Wagner [Carlini and Wagner 2017], however, it is only applicable to neural networks.

On the other hand, black-box attacks assume the attacker can only query the classifier, but not inspect its components such as support vectors or weights of a neural network. Attacks in this black-box model differ in what they assume about the output format: While the HopSkipJump attack by Chen et al. [Chen et al. 2019] only requires the class label and are therefore called decision-based, other attacks such as the Zeroth-order optimization attack [Chen et al. 2017] need the scores for each individual class and are referred to as score-based attacks. Additionally, Papernot et al. [Papernot et al. 2016a] studied the transferability of adversarial examples and found that substitute models generated by the adversary can be attacked in the white-box-model and the resulting examples are often adversarial for the target classifier as well.

According to Papernot et al. [Papernot et al. 2018], the problem of defending a classifier against adversarial attacks is not yet solved. We study one proposed method, adversarial training, where we re-train the target classifier on adversarial examples added to the training data. This method was introduced by Szegedy et al. [Szegedy et al. 2013] and we opted for this due to its simplicity.

In summary, while adversarial examples have been explored in the machine learning and security research communities, we are the first to study adversarial attacks and defense in the context of eye tracking and more specifically for eye-based user modelling.

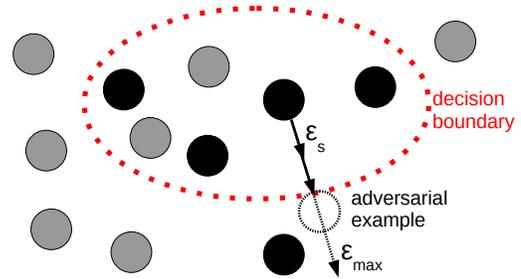


Figure 2: Illustration of how FGSM generates adversarial examples in 2D for a simple 2-class classification problem (black vs. gray points). The goal of the attack is to cross the decision boundary (red dotted line). FGSM computes the gradient and moves the point into this direction as shown with the black arrows. We used the minimal mode such that the data point is perturbed by multiples of ϵ_s iteratively until it is misclassified (here shown as dashed circle) or a maximal perturbation of ϵ_{max} is reached. In the example shown here, perturbation by twice ϵ_s is sufficient and it is not necessary to perturb the point by the maximal allowed amount ϵ_{max} .

3 CREATING ADVERSARIAL EXAMPLES FOR GAZE DATA

We model an attacker who knows the preprocessing pipeline and attacks at feature level. The targeted classifier might be known (white-box) or a suitable surrogate classifier can be trained.

To create adversarial examples, we used the Fast Gradient Sign Method [Goodfellow et al. 2014] (FGSM), a state-of-the-art method implemented in the Adversarial Robustness Toolbox [Nicolae et al. 2018]. As opposed to other state-of-the-art attacks like Carlini and Wagner [Carlini and Wagner 2017] or JASMA [Papernot et al. 2016b], FGSM does not rely on neural network structures but only on gradients that are well-defined for SVM with RBF kernel. Notice that RF did not have gradients and can therefore not be attacked by FGSM directly, only indirectly by transferability.

FGSM computed the gradient and perturbed the sample to move it along this direction. FGSM can be performed in two modes: standard and minimal. While the former implements FGSM as described in the paper by Goodfellow et al. [Goodfellow et al. 2014], the minimal mode repeatedly computes a growing adversarial perturbation until the sample is misclassified or a maximal perturbation is reached. Because the minimal attack leads to smaller perturbations in general, we applied this form of attack.

The minimal FGSM attack has three hyperparameters that need to be optimised: the norm to measure perturbations, the perturbation per step (ϵ_s), and the maximal perturbation (ϵ_{max}). Figure 2 visualizes FGSM with these hyperparameters. We used the L_2 norm to measure perturbations, which is often used for the generation of adversarial examples and can remain small if there are many small changes to the features [Carlini and Wagner 2017].

We evaluated two different methods to find the hyperparameters for FGSM, concretely, the maximal perturbation ϵ_{max} we allowed for adversarial examples. The general ϵ_{max} was chosen such that the average accuracy over multiple participants was lowest, this

corresponds to an attack without prior knowledge about the target’s data. We chose the person-specific ϵ_{max} by determining the maximal perturbation that was needed for the lowest accuracy for each person individually. Given that the lowest accuracy might not be necessary in all use-cases, we additionally evaluated how much perturbation was needed to drop the accuracy to chance level.

In order to evaluate the untargeted attack, we perturbed all samples independently of their ground truth label and the goal was to misclassify the sample into any of the other classes. In contrast, targeted attacks were evaluated on samples of one class only and the goal was to perturb them such that they were classified as one specific other class. Additionally, we studied transferability by evaluating the adversarial examples generated for SVM on a random forest classifier fitted on the same data. The SVM serves as surrogate classifier for the random forest.

4 EVALUATION

4.1 Dataset

In this work we used the public dataset by Steil et al. that included recordings of 20 participants reading three different types of document (comic, newspaper, textbook) in virtual reality [Steil et al. 2019a]. Eye movements were recorded using the eye tracking integration from Pupil Labs at 30Hz [Kassner et al. 2014]. The data includes detected eye positions in x- and y-direction in the range of [0,1], the estimated pupil diameter, the timestamp and how confidently these estimates were detected.

We first detected fixations using a dispersion-based algorithm. A fixation was detected if x- and y-positions of gaze samples were within a radius of 0.05 for at last three consecutive frames, i.e., 0.1 seconds and x- and y- positions were not both equal to zero. If x- and y-positions were both equal to zero and the confidence was zero for at last three consecutive frames, we recognized a blink. Notice that if the eye tracker could not detect the eyes, it returned zero for both x- and y-position as well as confidence. We assumed saccades between two fixations, or between fixations and blinks. We excluded saccades between fixations and blinks if there is not at least one frame in between to avoid situations where a fixation was directly followed by a blink and a saccade between fixation and blink is recognized. We followed the same approach for blinks directly followed by a fixation.

In a second step, we extracted a total of 52 high-level features from these basic eye movements as described by Bulling et al. [Bulling et al. 2010]. These features included the ratio of the detected features, means and variances of durations and pupil diameters as well as wordbook features that encode sequences of up to four saccades. Table 2 explains these features in detail. We extracted these features using a sliding window with the window size being one of the to-be-optimised hyperparameters of our method. Additionally, we added two more features from Kunze et al. [Kunze et al. 2013b], namely, the euclidean distance between the 5% and 95% quantile of fixation coordinates and the slope of saccade directions using linear regression over fixations. These features give a general estimate of the reading direction and distance covered during the time window.

4.2 Classifier Training

SVM Training. We studied the computational task of recognising different document types from eye movements during reading. Support vector machines (SVM) are a widely used classifier in the literature on eye-based user modelling [Bulling et al. 2010, 2013; Karessli et al. 2017; Sattar et al. 2015]. We trained with leave-one-person-out cross-validation using sklearn’s SVM implementation [Buitinck et al. 2013]. The optimal window size was selected based on validation accuracy of 200 samples per participant and document type. We found a window size of 45 seconds to perform best. Notice that we did not tune the penalty parameter C on the error term but kept its default parameter 1.0. We also did not tune the RBF-kernel hyperparameter γ that controls the locality of the kernel and used its default value of $\frac{1}{54}$. We report the accuracy on the remaining test samples (about 600 samples) per participant and document type for the selected window.

Random Forest Training. Decision-tree based classifiers such as random forest (RF) are also used in the eye tracking literature, e.g., in Kunze et al. [Kunze et al. 2013b] even though less frequently than SVMs. We study random forests as an example of adversarial example transferability across different types of classifiers. Similarly to before, we selected the best window size using leave-one-person-out cross-validation on the same data split into training, validation, and test data. Again, we found a window size of 45 seconds to perform best. We evaluated for the key hyperparameters, namely the number of trees (100, 50, 10, 200) and the number of samples per leaf (50, 10, 100, 5). Both measures are important to avoid overfitting.

4.3 Evaluation Metrics

We evaluate our attacks in terms of success, i.e., document type classification accuracy on adversarial examples, and in terms of changes induced. In order to evaluate the effect of the resulting perturbations, we compared the average distance between benign test samples to the distance between the benign and resulting adversarial point at feature level. We used again the L_2 distance metric as for the FGSM optimization. In case the average distances between benign and adversarial points were higher than the average distances between benign samples, we cannot call the adversarial perturbations “small” and conclude an attack significantly deteriorates data quality. To show the distances to adversarial examples are significantly lower than between benign samples, we applied scipy’s implementation [Jones et al. 2001] of Welch’s t-test, a test whether the two distributions have the same average value, but that does not assume identical variances.

5 RESULTS

Attack Success: Figure 3 shows the results of the targeted and untargeted white-box attacks on SVMs using FGSM. The accuracy after attack is well below chance level of $\frac{1}{3}$ with one exception, the targeted attack to misclassify newspaper as textbook where the accuracy is only around 0.4. But even in this case, the accuracy decreased massively from initially between 0.8 and 0.9. We conclude that the SVM is vulnerable to our attack.

We observe in Table 1 that the accuracy of general and person-specific choice of ϵ_{max} are very close and therefore plotted the

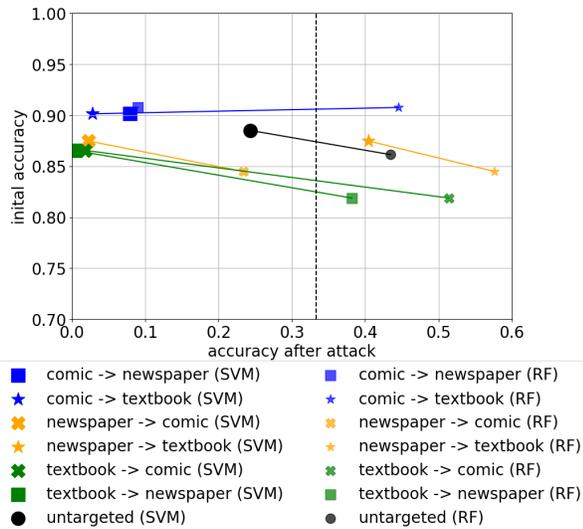
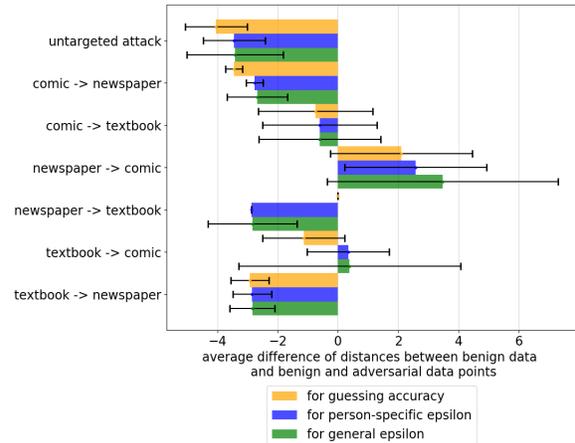


Figure 3: Accuracies after attacks on SVM with FGSM (larger markers) and transfer to RF (smaller markers). The y-axis displays the initial accuracy on benign data and the x-axis shows the performance on adversarial examples. Different colors and markers show different document types under attack. The dashed black line visualizes the chance level.

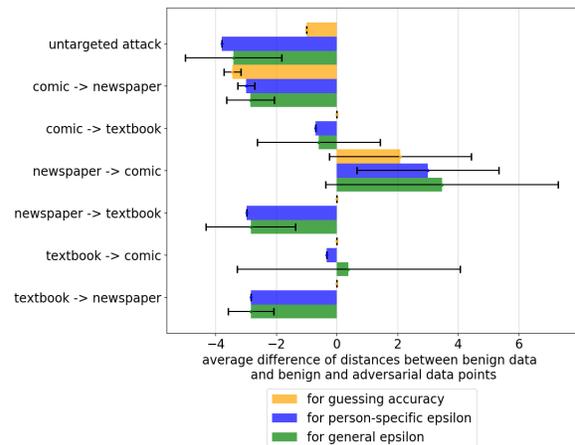
general choice of ϵ_{max} in Figure 3. That means, it is not necessary to know data of the target before mounting a successful attack.

Additionally, we compare the different target classes in Figure 3. It is easiest to perturb textbook samples such that they look like newspaper readings to the SVM, but textbook examples are also relatively easy to turn into the other class, comics. For comic, it is easier to trick the SVM into classifying it as textbook as newspaper. The newspaper examples are hard to turn into textbook samples, but can be misclassified as comic much easier. This is surprising because the reverse direction, perturbing a textbook example such that it is misclassified as newspaper, is the easiest in our study.

Distance Evaluation: Next, we evaluate the consequences of our adversarial perturbation in terms of euclidean distance. We first measured the euclidean distance between all test samples before the attack. This naturally occurring distance between samples was compared to the distances between test samples and their corresponding perturbed version. Table 1 reports the resulting distances, and we plotted the difference of distances in Figure 4a, i.e., average distance after attack minus the average distance of benign samples. A value positive value shows that the distance between benign and respective perturbed point is larger than the distance between benign points on average. The different coloured bars in Figure 4a show different ways to select the FGSM hyperparameter ϵ_{max} . Additionally, we selected the smallest ϵ_{max} such that on average over all participants, an accuracy of 0.3 is reached. Notice that this was not always possible and we show no orange bar in that case. If the goal is only guessing accuracy, smaller perturbations often suffice. We observe that in most cases, on average the distance between original and perturbed point is smaller than the average distance between benign test points. The p-values of Welch’s t-test between



(a) Difference of distances after untargeted and targeted attacks on SVM with FGSM.



(b) Difference of distances after untargeted and targeted attack on SVM and transfer to RF.

Figure 4: The x-axis shows the average distance of adversarial examples to their original benign point minus the average distance between benign points, bars towards the left indicate the adversarial example is closer to the benign point than the distances naturally occurring between test points, bars towards the right indicate the perturbations exceed these test point distances. Error bars visualize the standard deviation computed over the 20 participants. The y-axis shows untargeted attacks and the different targeted attacks that perturb samples from the first given class to be mistaken as the second class.

the two distributions of distances are below 0.01 except for the targeted attacks misclassifying comic as textbook and textbook as comic, respectively. This demonstrates that the perturbations we computed are indeed mostly “small”.

Transferability: Finally, we study whether the perturbations we computed carry over to a different family of classifiers, namely, RF classifiers. For that, we used the adversarial examples against the

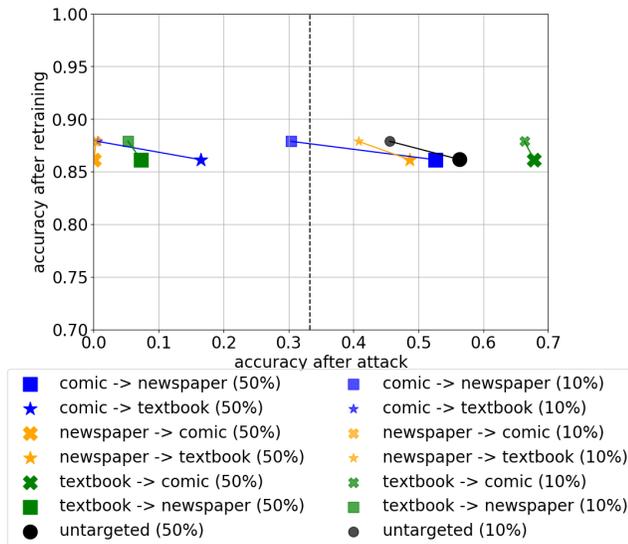


Figure 5: The y-axis shows the accuracy after retraining without adversarial examples and the x-axis shows the performance on adversarial examples crafted for the retrained SVM. Different colors and markers show different document types under attack. Retraining with 50% of the training data is displayed with larger markers, retraining with 10% with smaller markers. The dashed black line visualizes the chance level.

SVM computed as before but classified them with the RF, Figure 3 visualizes the results. Initially, SVM and RF had similar accuracy without the presence of adversarial examples. We observe that the accuracy drops after the attack, but only rarely below guessing accuracy for RF. That means, the decision boundaries between SVMs and RF are similar enough for some samples to be transferable, however, not so similar that all of them carry over. We show the distances' evaluation again in Figure 4b for RF. The distances are quite similar to those observed for the SVM, but in some cases higher. In these cases, a larger perturbation that was not necessary for SVM led to misclassification in the RF. We conclude that knowledge on the type of classifier does increase attack accuracy, however, hiding the type of classifier does not mitigate all attacks.

5.1 Defense with Adversarial Training

Our previous analyses demonstrated the fundamental vulnerability of classifiers to adversarial attacks. But following the idea of "fighting fire with fire", can adversarial examples in turn also be used to protect from such attacks? The goal of our final evaluation was to study the idea of using FGSM to protect SVM classifiers by retraining them on adversarial examples. We focused on the SVM classifier and the feature-level attack here because this was the most vulnerable setting.

We trained the SVM as before. Then, we randomly chose some percentage of the training data to generate adversarial examples and trained a new SVM on the original training data and the adversarial examples. We did not target the adversarial examples to any specific

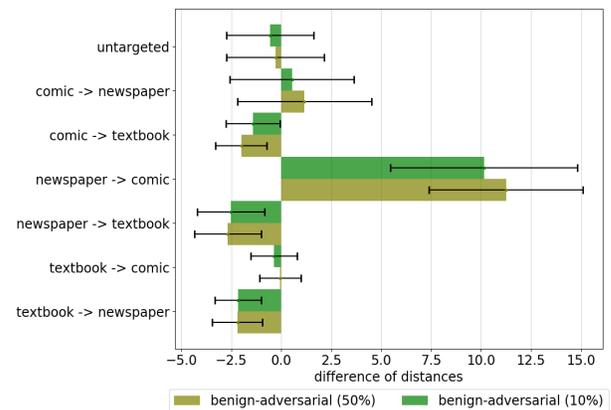


Figure 6: Difference of distances after untargeted and targeted attack on SVM that was retrained with adversarial examples. The bars show the difference between the average distances between benign test points and between benign and respective adversarial example, the error bars visualize the standard deviation.

class. As before, we report accuracy before and after the attack and calculate the distances between benign test samples and the respective adversarial samples. Additionally, we also measured the accuracy after retraining and compare it to the accuracy without retraining to ensure the SVM was not rendered useless due to the insertion of adversarial training data. We kept $\epsilon_s = 0.1$ and set ϵ_{max} to 2.0, the highest perturbation we used for the previous attacks. Preliminary experiments showed that the percentage of training data that was added to the training dataset has the highest influence on attack success. We therefore evaluate for two amounts: adding 10% and adding 50% of adversarial examples to the training set.

Figure 5 summarises the results of this evaluation. In untargeted mode and for some targeted attacks the accuracy remains between 0.4 and 0.7. That is, in these cases the training with adversarial examples is effective in protecting the SVM classifier. However, some targeted attacks are still successful and pull the accuracy below chance level. It is important to note that the accuracy after retraining remains similar to the initial accuracy (see also Table 1). This shows that adding adversarial examples to the training data set does not harm the overall utility of the classifier.

When comparing distances, Figure 6 shows that the distances between adversarial and benign data is larger due to retraining. Especially for the targeted attack on newspaper to flip the label to comic, the attack is successful, but at a very large perturbation clearly exceeding the benign distances. This underlines the potential of training on adversarial examples as a first line of defence against adversarial attacks.

6 DISCUSSION

6.1 On Adversarial Attacks

Our evaluations highlight a serious problem that has so far been neglected in the eye tracking community: We demonstrated that

current classifiers for eye-based user modelling are not trustworthy because of their vulnerability to adversarial examples. For the envisioned future application of eye-based user modelling for life logging and quantified self, this means that collected gaze behaviour statistics currently can be tampered with without the user noticing it. More seriously, for future use of eye tracking and eye-based user modelling in the medical domain [Holzman et al. 1974; Vidal et al. 2012b] this finding means that users currently cannot be certain that diagnostic predictions are correct before starting a respective treatment.

Our evaluations also showed that “security by obscurity” is not a solution. Even if the type of classifier is unknown to the adversary, the classifier is still vulnerable (see Figure 3). We are confident that hiding the training data is not a solution either, even though we could not test this strategy in this work due to the lack of a suitable, larger dataset. Given that eye tracking researchers increasingly publish their gaze datasets, potential attackers already have access to large amounts of training data anyway.

6.2 On Defending against Adversarial Attacks

Robustness of classifiers is well studied in the machine learning and security community and researchers have explored many attack vectors and defence mechanisms. It is an open question whether their findings that are predominantly on images carry over to eye data. As a first step to answering this question, we explored adversarial retraining. We found it partially successful and due to the easy generation of adversarial examples with FGSM this method is also usable in practice. Even better, the detailed analysis of the different document types demonstrated that some documents can be classified better in presence of adversarial perturbations. As a nice side effect we observed that this method does not cost utility, i.e., the classification accuracy does not drop. This might be simply due to the fact that more data is available, especially in those areas where the classifier would otherwise lack training data. Therefore, adversarial examples might also be used as a way to augment training data and generate high performance classifiers.

6.3 On Recommendations

We recommend practitioners to carefully test their classifiers for vulnerabilities to adversarial examples before fully trusting their outputs. Especially if gradients are available for the classifiers, the overhead of generating adversarial examples from test data with FGSM is only 0.05 seconds per sample. Retraining with 10% of the training data as explained in subsection 5.1 takes 4-5 minutes. Compared to under one minute for training without adversarial examples, this is a manageable overhead. Notice that these measurements were made on a laptop without the use of multithreading. If vulnerabilities are found, adding adversarial examples to training data might be a first line of defense that is feasible to implement. Furthermore, we suggest eye tracking researchers to study the characteristics of adversarial examples, are these fundamentally different from benign data such that they can be easily detected? Or do adversarial examples point to regions where training data is sparse and can therefore be used to augment the training set for better classification qualities?

6.4 On Limitations

Our evaluations provide valuable new insights into a fundamental vulnerability of current classifiers for eye-based user modelling. Nevertheless, future work could address a number of limitations in the current study. First, all of our findings are based on the 20-participant dataset from [Steil et al. 2019a]. While the dataset size is not uncommon and allows for meaningful analyses, it is clear that with a view to further and potentially more sophisticated analyses, the collection of larger and more diverse datasets will be crucial. A second limitation is in the studied reading task. While reading is a truly pervasive activity and has therefore been studied early on in eye-based user modelling [Bulling et al. 2012, 2008], it will be interesting to see whether everyday activities are more diverse and corresponding classifiers will therefore be harder to attack. Third, our attack on raw data was tested only with one common eye movement event detection algorithm. Future work could explore whether other event detection methods, e.g., velocity-based instead of dispersion, can be more robust to adversarial attacks. Finally, future work could study the applicability of other defense mechanisms to eye tracking classifiers than the adversarial training proposed here, such as defensive distillation [Papernot et al. 2016c].

7 CONCLUSION

In this work we studied adversarial examples – a novel attack vector in the emerging field of privacy-aware eye tracking. Specifically, we demonstrated the vulnerability of two commonly used classifiers for eye-based user modelling to adversarial examples on the sample task of eye-based document type classification. The identified vulnerabilities underline the urgent need for further research on more robust gaze data classifiers for eye-based user modelling. As a first step in this direction, we demonstrated that training with a small amount of adversarial examples can be effective for hardening SVM classifiers against adversarial attacks.

REFERENCES

- Lars Buitinck, Gilles Louppe, Mathieu Blondel, Fabian Pedregosa, Andreas Mueller, Olivier Grisel, Vlad Niculae, Peter Prettenhofer, Alexandre Gramfort, Jaques Grobler, Robert Layton, Jake VanderPlas, Arnaud Joly, Brian Holt, and Gaël Varoquaux. 2013. API design for machine learning software: experiences from the scikit-learn project. In *ECML PKDD Workshop: Languages for Data Mining and Machine Learning*. 108–122.
- Andreas Bulling, Daniel Roggen, and Gerhard Tröster. 2011. What’s in the Eyes for Context-Awareness? *IEEE Pervasive Computing* 10, 2 (2011), 48–57. <https://doi.org/10.1109/MPRV.2010.49>
- Andreas Bulling, Jamie A. Ward, and Hans Gellersen. 2012. Multimodal Recognition of Reading Activity in Transit Using Body-Worn Sensors. *ACM Transactions on Applied Perception* 9, 1 (2012), 2:1–2:21. <https://doi.org/10.1145/2134203.2134205>
- Andreas Bulling, Jamie A. Ward, Hans Gellersen, and Gerhard Tröster. 2008. Robust Recognition of Reading Activity in Transit Using Wearable Electrooculography. In *Proc. International Conference on Pervasive Computing (Pervasive)*. 19–37. https://doi.org/10.1007/978-3-540-79576-6_2
- Andreas Bulling, Jamie A Ward, Hans Gellersen, and Gerhard Troster. 2010. Eye movement analysis for activity recognition using electrooculography. *IEEE transactions on pattern analysis and machine intelligence* 33, 4 (2010), 741–753.
- Andreas Bulling, Christian Weichel, and Hans Gellersen. 2013. EyeContext: recognition of high-level contextual cues from human visual behaviour. In *Proceedings of the sigchi conference on human factors in computing systems*. ACM, 305–308.
- Andreas Bulling and Thorsten O Zander. 2014a. Cognition-aware computing. *IEEE Pervasive Computing* 13, 3 (2014), 80–83.
- Andreas Bulling and Thorsten O. Zander. 2014b. Cognition-Aware Computing. *IEEE Pervasive Computing* 13, 3 (2014), 80–83. <https://doi.org/10.1109/mprv.2014.42>
- Nicholas Carlini and David Wagner. 2017. Towards evaluating the robustness of neural networks. In *2017 IEEE Symposium on Security and Privacy (SP)*. IEEE, 39–57.

- Jianbo Chen, Michael I Jordan, and Martin J Wainwright. 2019. HopSkipJumpAttack: A query-efficient decision-based attack. *arXiv preprint arXiv:1904.02144* (2019).
- Pin-Yu Chen, Huan Zhang, Yash Sharma, Jinfeng Yi, and Cho-Jui Hsieh. 2017. Zoo: Zeroth order optimization based black-box attacks to deep neural networks without training substitute models. In *Proceedings of the 10th ACM Workshop on Artificial Intelligence and Security*. ACM, 15–26.
- Nilesh Dalvi, Pedro Domingos, Sumit Sanghai, Deepak Verma, et al. 2004. Adversarial classification. In *Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining*. ACM, 99–108.
- Ian J Goodfellow, Jonathon Shlens, and Christian Szegedy. 2014. Explaining and harnessing adversarial examples. *arXiv preprint arXiv:1412.6572* (2014).
- Eckhard H Hess and James M Polt. 1960. Pupil size as related to interest value of visual stimuli. *Science* 132, 3423 (1960), 349–350.
- Corey Holland and Oleg V Komogortsev. 2011. Biometric identification via eye movement scanpaths in reading. In *2011 International joint conference on biometrics (IJCB)*. IEEE, 1–8.
- Philip S Holzman, Leonard R Proctor, Deborah L Levy, Nicholas J Yasillo, Herbert Y Meltzer, and Stephen W Hurt. 1974. Eye-tracking dysfunctions in schizophrenic patients and their relatives. *Archives of general psychiatry* 31, 2 (1974), 143–151.
- Sabrina Hoppe, Tobias Loetscher, Stephanie A Morey, and Andreas Bulling. 2018. Eye movements during everyday behavior predict personality traits. *Frontiers in human neuroscience* 12 (2018), 105.
- Young-Min Jang, Rammohan Mallipeddi, and Minho Lee. 2014. Identification of human implicit visual search intention based on eye movement and pupillary analysis. *User Modeling and User-Adapted Interaction* 24, 4 (2014), 315–344.
- Brendan John, Sanjeev Koppal, and Eakta Jain. 2019. EyeVELL: degrading iris authentication in eye tracking headsets. In *Proceedings of the 11th ACM Symposium on Eye Tracking Research & Applications*. ACM, 37.
- Eric Jones, Travis Oliphant, Pearu Peterson, et al. 2001. SciPy: Open source scientific tools for Python. (2001).
- Nour Kaessli, Zeynep Akata, Bernt Schiele, and Andreas Bulling. 2017. Gaze embeddings for zero-shot image classification. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 4525–4534.
- Moritz Kassner, William Patera, and Andreas Bulling. 2014. Pupil: an open source platform for pervasive eye tracking and mobile gaze-based interaction. In *Adj. Proc. ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp)*. 1151–1160. <https://doi.org/10.1145/2638728.2641695>
- Craig A Kuechenmeister, Patrick H Linton, Thelma V Mueller, and Hilton B White. 1977. Eye tracking in relation to age, sex, and illness. *Archives of General Psychiatry* 34, 5 (1977), 578–579.
- Kai Kunze, Masakazu Iwamura, Koichi Kise, Seiichi Uchida, and Shinichiro Omachi. 2013a. Activity recognition for the mind: Toward a cognitive "Quantified Self". *Computer* 46, 10 (2013), 105–108.
- Kai Kunze, Katsutoshi Masai, Masahiko Inami, Ömer Sacakli, Marcus Liwicki, Andreas Dengel, Shoya Ishimaru, and Koichi Kise. 2015. Quantifying reading habits: counting how many words you read. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing*. ACM, 87–96.
- Kai Kunze, Yuzuko Utsumi, Yuki Shiga, Koichi Kise, and Andreas Bulling. 2013b. I know what you are reading: recognition of document types using mobile eye tracking. In *Proceedings of the 2013 International Symposium on Wearable Computers*. ACM, 113–116.
- Daniel J Liebling and Sören Preibusch. 2014. Privacy considerations for a pervasive eye tracking world. In *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct Publication*. ACM, 1169–1177.
- Ao Liu, Lirong Xia, Andrew Duchowski, Reynold Bailey, Kenneth Holmqvist, and Eakta Jain. 2019. Differential privacy for eye-tracking data. In *Proceedings of the 11th ACM Symposium on Eye Tracking Research & Applications, ETRA 19*. ACM.
- Daniel Lowd and Christopher Meek. 2005. Adversarial learning. In *Proceedings of the eleventh ACM SIGKDD international conference on Knowledge discovery in data mining*. ACM, 641–647.
- G Matthews, W Middleton, B Gilmartin, and MA Bullimore. 1991. Pupillary diameter and cognitive load. *Journal of Psychophysiology* (1991).
- Maria-Irina Nicolae, Mathieu Sinn, Minh Ngoc Tran, Beat Buesser, Ambrish Rawat, Martin Wistuba, Valentina Zantedeschi, Nathalie Baracaldo, Bryant Chen, Heiko Ludwig, Ian Molloy, and Ben Edwards. 2018. Adversarial Robustness Toolbox v1.0.1. *CoRR* 1807.01069 (2018). <https://arxiv.org/pdf/1807.01069>
- Ishan Nigam, Mayank Vatsa, and Richa Singh. 2015. Ocular biometrics: A survey of modalities and fusion approaches. *Information Fusion* 26 (2015), 1–35.
- Nicolas Papernot, Patrick McDaniel, and Ian Goodfellow. 2016a. Transferability in machine learning: from phenomena to black-box attacks using adversarial samples. *arXiv preprint arXiv:1605.07277* (2016).
- Nicolas Papernot, Patrick McDaniel, Somesh Jha, Matt Fredrikson, Z Berkay Celik, and Ananthram Swami. 2016b. The limitations of deep learning in adversarial settings. In *2016 IEEE European Symposium on Security and Privacy (EuroS&P)*. IEEE, 372–387.
- Nicolas Papernot, Patrick McDaniel, Arunesh Sinha, and Michael P Wellman. 2018. SoK: Security and privacy in machine learning. In *2018 IEEE European Symposium on Security and Privacy (EuroS&P)*. IEEE, 399–414.
- Nicolas Papernot, Patrick McDaniel, Xi Wu, Somesh Jha, and Ananthram Swami. 2016c. Distillation as a defense to adversarial perturbations against deep neural networks. In *2016 IEEE Symposium on Security and Privacy (SP)*. IEEE, 582–597.
- Negar Sammaknejad, Hamidreza Pourtemad, Changiz Eslahchi, Alireza Salahirad, and Ashkan Alinejad. 2017. Gender classification based on eye movements: A processing effect during passive face viewing. *Advances in cognitive psychology* 13, 3 (2017), 232.
- Hosnieh Sattar, Andreas Bulling, and Mario Fritz. 2017a. Predicting the Category and Attributes of Visual Search Targets Using Deep Gaze Pooling. In *Proc. IEEE International Conference on Computer Vision Workshops (ICCVW)*. 2740–2748. <https://doi.org/10.1109/ICCVW.2017.322>
- Hosnieh Sattar, Mario Fritz, and Andreas Bulling. 2017b. *Visual Decoding of Targets During Visual Search From Human Eye Fixations*. Technical Report.
- Hosnieh Sattar, Sabine Müller, Mario Fritz, and Andreas Bulling. 2015. Prediction of Search Targets From Fixations in Open-world Settings. In *Proc. IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. 981–990. <https://doi.org/10.1109/CVPR.2015.7298700>
- Julian Steil and Andreas Bulling. 2015. Discovery of everyday human activities from long-term visual behaviour using topic models. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing*. ACM, 75–85.
- Julian Steil, Inken Hagestedt, Michael Xuelin Huang, and Andreas Bulling. 2019a. Privacy-aware eye tracking using differential privacy. In *Proceedings of the 11th ACM Symposium on Eye Tracking Research & Applications, ETRA 19*. ACM, 27.
- Julian Steil, Marion Koelle, Wilko Heuten, Susanne Boll, and Andreas Bulling. 2019b. Privacy-aware eye tracking using differential privacy. In *Proceedings of the 11th ACM Symposium on Eye Tracking Research & Applications*. ACM, 26.
- Christian Szegedy, Wojciech Zaremba, Ilya Sutskever, Joan Bruna, Dumitru Erhan, Ian Goodfellow, and Rob Fergus. 2013. Intriguing properties of neural networks. *arXiv preprint arXiv:1312.6199* (2013).
- Marc Tonsen, Julian Steil, Yusuke Sugano, and Andreas Bulling. 2017. InvisibleEye: Mobile Eye Tracking Using Multiple Low-Resolution Cameras and Learning-Based Gaze Estimation. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies (IMWUT)* 1, 3 (2017), 106:1–106:21. <https://doi.org/10.1145/3130971>
- Mélo die Vidal, Jayson Turner, Andreas Bulling, and Hans Gellersen. 2012a. Wearable Eye Tracking for Mental Health Monitoring. *Computer Communications* 35, 11 (2012), 1306–1311. <https://doi.org/10.1016/j.comcom.2011.11.002>
- Mélo die Vidal, Jayson Turner, Andreas Bulling, and Hans Gellersen. 2012b. Wearable eye tracking for mental health monitoring. *Computer Communications* 35, 11 (2012), 1306–1311.
- Gregory J Zelinsky, Yifan Peng, and Dimitris Samaras. 2013. Eye can read your mind: Decoding gaze fixations to reveal categorical search targets. *Journal of vision* 13, 14 (2013), 10–10.
- Xucong Zhang, Yusuke Sugano, and Andreas Bulling. 2017. Everyday Eye Contact Detection Using Unsupervised Gaze Target Discovery. In *Proc. ACM Symposium on User Interface Software and Technology (UIST)*. 193–203. <https://doi.org/10.1145/3126594.3126614>
- Xucong Zhang, Yusuke Sugano, Mario Fritz, and Andreas Bulling. 2019. MPIIGaze: Real-World Dataset and Deep Appearance-Based Gaze Estimation. *IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI)* 41, 1 (2019), 162–175. <https://doi.org/10.1109/TPAMI.2017.2778103>

metric	attack type	target	untargeted	comic classified as		newspaper classified as		textbook classified as	
				newspaper	textbook	comic	textbook	comic	newspaper
feature level attacks									
accuracy	initial	SVM	0.89	0.90	0.90	0.87	0.87	0.87	0.87
	general ϵ_{max}	SVM	0.24	0.08	0.03	0.02	0.40	0.02	0.00
	individual ϵ_{max}	SVM	0.24	0.07	0.03	0.02	0.40	0.02	0.00
accuracy	initial	RF	0.86	0.91	0.91	0.84	0.84	0.82	0.82
	general ϵ_{max}	RF	0.43	0.09	0.45	0.23	0.58	0.51	0.38
	individual ϵ_{max}	RF	0.43	0.09	0.44	0.23	0.58	0.48	0.38
distance	benign	SVM	7.76	5.94	5.94	5.42	5.42	4.59	4.59
	individual ϵ_{max}	SVM	4.32	3.18	5.34	7.99	2.55	4.93	1.75
	general ϵ_{max}	SVM	4.35	3.27	5.34	8.89	2.58	4.97	1.75
	guess	SVM	3.73	2.49	5.20	7.51	-	3.45	1.67
distance	benign	RF	7.76	5.94	5.94	5.42	5.42	4.59	4.59
	individual ϵ_{max}	RF	3.97	2.95	5.24	8.42	2.45	4.25	1.75
	general ϵ_{max}	RF	4.35	3.08	5.34	8.89	2.58	4.97	1.75
	guess	RF	-	2.49	-	7.51	-	-	-
retrain attacks									
accuracy	10% initial	SVM	0.89	0.95	0.95	0.86	0.86	0.84	0.84
	10% retrain	SVM	0.88	0.88	0.88	0.88	0.88	0.88	0.88
	10% attack	SVM	0.46	0.30	0.01	0.00	0.41	0.66	0.05
accuracy	50% initial	SVM	0.89	0.94	0.94	0.84	0.84	0.81	0.81
	50% retrain	SVM	0.86	0.86	0.86	0.86	0.86	0.86	0.86
	50% attack	SVM	0.56	0.53	0.16	0.00	0.49	0.68	0.07
distance	10% benign	SVM	7.76	5.94	5.94	5.42	5.42	4.59	4.59
	10% attack	SVM	7.20	6.48	4.54	15.56	2.91	4.23	2.44
distance	50% benign	SVM	7.76	5.94	5.94	5.42	5.42	4.59	4.59
	50% attack	SVM	7.47	7.10	3.94	16.67	2.75	4.54	2.39

Table 1: Summaries of results for the different types of attacks

feature type	explanation	number of features
Fixation	rate, computed over pupil positions within one fixation: mean, max, variance of durations, mean of mean, variance of variance	8
Saccades	rate, ratio of (small/large/right/left) saccades, mean, max and variance of amplitudes	12
Combined	ratio saccades to fixations	1
Wordbooks	for n-grams of length up to four (including): number of non-zero entries, maximum and minimum of entries	24
Blinks	rate, mean and variance of blink duration	3
Pupil Diameter	mean of mean and variance of variance during fixations	4
reading features	euclidean distance between the 5% and 95% quantile of fixation coordinates, the slope of saccade directions using linear regression over fixations	2

Table 2: We extracted 54 eye movement features to describe a user’s eye movement behaviour based on the 52 features by Steil et al. [Steil et al. 2019a] and 2 features from Kunze et al. [Kunze et al. 2013b]