Fantômas: Evaluating Reversibility of Face Anonymizations Using a General Deep Learning Attacker

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Abstract

Biometric data is a rich source of information that can be used to identify individuals and infer private information about them. To mitigate this privacy risk, anonymization techniques employ transformations on clear data to obfuscate sensitive information, all while retaining some utility of the data. Albeit published with impressive claims, they sometimes are not evaluated with convincing methodology. We hence are interested to which extent recently suggested anonymization techniques for obfuscating facial images are effective. More specifically, we test how easily they can be automatically reverted, to estimate the privacy they can provide. Our approach is agnostic to the anonymization technique as we learn a machine learning model on the clear and corresponding anonymized data. We find that 10 out of 14 tested face anonymization techniques are at least partially reversible, and six of them are at least highly reversible.

1 Introduction

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In today's world, biometric data is pervasively captured as more sensors are recording us in larger quantity and quality. Take, for example, the increasing usage of surveillance cameras, autonomous vehicles that scan their surroundings, mixed reality devices, or sensors in various smart devices. This development poses challenges to individual privacy, as extensive sensitive information can be inferred from our biometric data. Examples are abound, and they include identity, personal preferences, political opinions, sexuality, or health status and medical conditions. Some suggested biometric data protection techniques attempt to prevent this threat. One class of these systems aims at irreversibly transforming the data in such a way that privacy-sensitive inferences are no longer possible, while trying to retain the utility of the data. There are many proposals on how to design such privacy protection techniques, however, the evaluation methodology to quantify how much privacy protection they offer is still lacking.

Our main contribution in this paper is the proposal of an evaluation methodology that tests the irreversibility of biometric data protection techniques. We do so by assuming a strong attacker that is aware of the privacy protection in place and who has access to clear and the corresponding anonymized data. We then train a machine learning model to learn a transformation from the anonymized data to the clear data. The clear, anonymized, and de-anonymized data are then tested against a biometric recognition system to see if the de-anonymization was successful. The benefit of our approach is its generality, which allows us to quickly adapt it to a new anonymization by training a new model for it, allowing us to test reversibility on many anonymizations.

Our contributions are as follows:

- A general methodology to test irreversibility of biometric data anonymization;
- the concrete application of the methodology to face anonymization;
- irreversibility results of a large number of face

We observe a severe problem with the current evaluation methodology: they frequently rely on weak attacker models that assume an attacker unaware of the protection measures. An attacker who is aware of data modifications is stronger (and we claim: more realistic!) as they can actively try to remove the protection. We see two main directions an attacker can pursue. The first one evaluates the mechanism for efficacy, by training the recognition system on a combination of clear and protected data, instead of the commonly implemented training solely on clear data. This helps to adapt it to changes that are due to the protection mechanism. A notable initiative exploring this direction is the VoicePrivacy challenge [46]. Evaluating for invertibility represents an alternative direction: it aims to develop an algorithm to invert the protected data back to clear data. Preventing inversion is a key requirement of biometric data protection, but it is often overlooked when evaluating privacy mechanisms. We hence propose a methodology to test it in this work.

anonymization techniques;

 a user-study to validate our irreversibility results against human observers.

Our work is structured as follows. First we explain the background for our work in Section 2 before we review the related literature in Section 3. We then describe our general approach in in Section 4 including the attacker model and evaluation methodology. In Section 5 we then show how we apply our methodology to the field of face anonymization and describe the used anonymization and specialized de-anonymization techniques in Section 6, which we evaluate in Section 7. We finish our work by discussing the limitations of our approach in Section 8 and draw a conclusion in Section 9.

2 Background

Here we present the background and terminology which is required to understand our work and the assumptions it is based on.

Following established vocabulary [17] we use biometric characteristics to describe the biological and behavioral characteristics that can be used to extract biometric features which in turn can be used by biometric recognition to identify individuals or infer attributes, such as age and gender about them. To prevent biometric recognition privacy enhancing technologies (PETs) are employed which obfuscate the private information in the data from internal and external observers. The specific term of anonymization refers to PETs which remove all identifiers that directly identify individuals. Anonymization takes biometric clear data as input and outputs **anonymized data**. For the remainder of this work, we will assume a data publishing model as our system model, as such the biometric data must be anonymized before it is published to a third party. This implies that the anonymization must not be reversible as else a malicious third party can simply remove the anonymization to access the data. An example of this system model would be a user who anonymizes their clear data before uploading it to a social media site. We will call anonymized data on which anonymization reversal was attempted **de-anonymized** data.

2.1 Anonymization evaluation state of the art

The most common evaluation methodology today to test the anonymization of biometric data is to measure the recognition accuracy with a biometric recognition system. By comparing the accuracy of the clear and anonymized data the protection of the anonymization can be determined. Newton et al. [28] proposed to differentiate these experiments by which data was used for enrollment and testing of the recognition system. In their approach, **naive recognition** uses clear data as enrollment data, and then both clear and anonymized data are used as test data. Parrot recognition on the other hand enrolls the recognition system on anonymized data before it is tested against anonymized data, which most of the time improves the performance as the recognition system can adapt to the anonymized data better. The parrot recognition approach was further improved by Srivastava et al. [42] who split the parrot recognition case into a semi-informed attacker who only knows the anonymization technique but not its parameters and an informed attacker who knows the anonymization technique and its exact parameters. A recent initiative to build a common methodology how to evaluate speaker anonymization is the VoicePrivacy [45] challenge. Similar to the methodologies above they define the attackers by how much access to anonymized training data they have. Besides evaluating against a biometric recognition system it is also possible to evaluate against human evaluators who try to recognize individuals.

3 Related Work

Template protection is closely related to biometric data anonymization as its goal is to remove all attributes, except the identity, from the data. ISO-23745 [1] requires template protection schemes to be irreversible. Cappelli et al. [4] reconstructed fingerprints from templates. De-anonymization attacks are a common threat to biometric template schemes as a survey by Gomez et al. [12] shows. Biometric data anonymization schemes share the same system model as template protection schemes and hence also must be irreversible to protect user privacy. However, the attacks on template protection schemes are not directly applicable as template protection schemes try to keep the identity of a subject while anonymizations try to remove them.

Evaluation methodology improvement is a common research subject, that is not only explored for biometric data anonymization but also in the field of biometric recognition. Philips et al. [32] suggested partitioning of the used biometric data set according to the quality of the data samples. The reasoning for this methodology is that it becomes easier to judge the robustness of recognition algorithms. Stolerman et al. [43] looked critically at the usage of a closed-world assumption for stylometry recognition. They found that many stylometry methods fail when an open-world assumption is utilized. Goga et al. [11] were able to show that the matching of profiles across social networks is not as easy as previously thought by making the assumptions in their evaluation more realistic. Arp et al. [2] had a look at the used methodologies for using machine learning in the security field and identified common mistakes. All these works highlight that it is important to critically look at the used evaluation methodologies to further drive the development of anonymization techniques towards better privacy protection.

Specialized reversibility attacks for biometric data anonymization techniques have been proposed in the past. Xu et al. [40] train a convolutional neural network to reconstruct blurred faces. Lu et al. [22] have proposed a super-resolution approach that removes pixelation from face images. A denoising and deblurring approach was proposed by Zamir et al. [51] who use an auto-encoder to recover a restored version of an image. Further methods performing deblurring are by Krishnan et al. [20], Pan et al. [31], and Tsai et al. [47]. Tekli et al. [44] have created a framework that evaluates image anonymization and can apply three different specialized reconstruction attacks on the images. Hao et al. [14] look at multiple anonymization techniques and use an image-to-image machine learning network to reconstruct some anonymized images. While for this specific use-case of deblurring and denoising images methods exist there are no methods that are generally applicable to biometric data anonymizations. Missing is also a systematic evaluation of how the reconstruction approach works against various types of anonymization.

4 Approach

In this section, we first explain why we require the evaluation of reversibility and then present our resulting attacker model. We then introduce our evaluation methodology.

4.1 Analysis

As we already mentioned in the introduction most evaluations of biometric data anonymizations assume a weak attacker which is not aware of the anonymization that was performed on the data. This is an unrealistic limitation of the attacker as anonymizations are often easy to detect (e.g. a blurred face) and we believe that a dedicated attacker will always be able to detect that the data is anonymized. Further, for PETs, we are most commonly interested in wort-case performance, so assuming a strong attacker is only natural.

With the attacker being aware of the anonymization they will try to reverse the obfuscation of the data, making irreversibility a mandatory feature for every anonymization. A strategy [28, 46] that has been proven to be successful for this is the retraining of biometric recognition systems using anonymized samples to adapt the model to the obfuscation. However, biometric recognition systems have never been designed for dealing with obfuscation and hence we believe that a dedicated approach to reverse the data obfuscation will be more successful. Looking at the literature we found that some specialized approaches to reverse anonymizations already exist (e.g. deblurring) and are successful giving indication that de-anonymization attacks might be possible against other anonymizations. However, developing specialized approaches for every anonymization to test would be time-consuming and the results wouldn't be directly comparable across anonymization methods. This is why we seek to develop a general deanonymization attacker for biometric data anonymization.

4.2 Attacker model

The goal of our attacker is to identify individuals in anonymized biometric recordings, by reverting the anonymization of the data. To achieve this goal the attacker knows that the recordings are anonymized, however, in order to make the attacker general and agnostic to the anonymization we regard the anonymization as a black box for which neither the parameters nor the anonymization method itself are known. Further, the attacker has access to a clear data set of biometric recordings which they can anonymize using the black box anonymization (similar to encryption oracles in cryptography) giving the attacker a corresponding anonymized data set. For the identification of individuals the attacker also posses clear enrollment data and anonymized test data. A visual example of the data sets in our attacker model can be found in Figure 1. The success of the attack will be measured by how well the attacker can identify the individuals in the test data set (not how well the anonymized data was de-anonymized). We consider the attacker to be successful if they can identify individuals in the de-anonymized recordings more successfully than in the anonymized recordings. A comparison of our attacker model to existing ones can be found in Table 1.

A simple real-world example of our attacker would be an attacker that tries to identify individuals on a social media site that anonymizes faces in images before they are shared online. By uploading its clear data set the attacker receives the corresponding anonymized data set and can then perform its de-anonymize attack.

Model	naive	parrot	specialized	ours	crypto
Knowledge of					
manipulation	X	1	1	1	1
manipul. method	X	×	1	X	1
manipul. parameters	X	×	1	X	(✔)
Access to data pairs	X	X	×	1	1

Table 1: Comparison of attacker models

4.3 Evaluation Methodology

Based on our attacker model, we design an evaluation methodology to test biometric data anonymization. The novel idea of the methodology is to perform general de-anonymization before the identification is tested on the data. To keep the deanonymization general we keep it agnostic to the anonymization under test by using machine learning to learn a model that transforms the anonymized data back into its corresponding clear data and therefore de-anonymizes the data. This way the



Figure 1: Data access of our attacker model

attacker can be easily adapted to a multitude of anonymizations.

After the training of the model, we use it to de-anonymize the test data which results in the de-anonymized test data. To now perform the identification we use a biometric recognition system in which we enroll clear data samples of the individuals we wish to identify and test against the de-anonymized test data (for a comparison to previous methodologies see Figure 2.). We select clear data as the enrollment data as we assume that due to the de-anonymization the de-anonymized data is closer to clear than anonymized data. This assumption was confirmed in an experiment (e.g. see Appendix 25). The identification accuracy of the recognition system of the deanonymized data is a metric of the anonymization method's ability to protect the privacy of individuals in the biometric recordings. If the recognition system is able to identify individuals, then either anonymized data is sufficient to identify individuals (the case caught by previous evaluation methodology) or the anonymization method was reversible.

In the next section, we propose a specific machine-learning model to evaluate anonymization for face images.



Figure 2: Recognition attacker models

5 Design

In the following, we describe the design of a general deanonymization attacker for face images. We are guided by two underlying processes: reconstruction and inversion. Reconstruction exploits the correlations and dependencies in the biometric data to recover removed information. Take for example face images in which due to the structure of the face it is clear where the position of the eyes is, or how the color of one eye most of the time also gives you the color of the other eye. Inversion on the other hand is the direct inversion of the operation that the anonymization performed on the data. A model trained to de-anonymize the data will use a combination of both.

Considering that both our input and output are images, we decide to select an under-complete auto-encoder as the base model. Auto-encoders compress the input into a small latent code that represents the input before decoding it back into the same domain as the input making them popular choices as a method to remove noise from images called denoising auto-encoders [13,41]. The benefit of auto-encoders is that the encoder and decoder learn the intrinsic dependencies in the data which can help with the reconstruction of data that was obfuscated by anonymization. A specialized version of auto-encoders that use this ability are auto-encoders which are used as generators for deepfakes [25,29].

For denoising, we find both auto-encoders with linear and convolutional layers being used. Many common face anonymization methods perform localized changes in the image and therefore convolutional layers with their locality and translation invariance properties seem like the obvious choice. In these cases, the dominant process is reconstruction. Convolutional layers are also the more common option whenever dealing with images as there exists the concept of neighborhoods and relative positions of pixels as opposed to linear layers that rather work with vectors and interpret them as simple lists of values. In situations in which convolutional layers can solve a problem, they should also generally be preferred over linear layers as they have fewer trainable parameters which will speed up the training process.

Our attacker's machine-learning model is supposed to be general enough to be able to reverse any anonymization method. Therefore it is not sufficient that "many" anonymizations only perform localized changes that can be reversed using convolutional layers. Very simple, deterministic anonymizations such as block permutation would not be reversible using only convolutional layers. This is because we are missing the inversion process. The locality principle of convolutional layers means that the output at a specific location only depends on the inputs at and around this location. But this means that a pixel at the top right cannot use the input at the bottom left which might be the relevant pixel in an image that was block permuted.

In linear layers, this locality principle does not exist and outputs can depend on any (or all) inputs including those that would not be considered close enough by a convolutional layer. Therefore, a machine learning model that was actually general, would have to use linear layers and not convolutional layers. However, linear layers require memory proportional to input size times output size. Considering that we are working with high-resolution RGB images we choose to use a model with a single linear layer between the encoder and decoder of our model to keep the model size feasible. A visual representation of the described model is shown in Figure 3.



Figure 3: Design of our machine learning model

In the encoder part, the model uses two convolutional layers with the following activation functions and max pooling layers. The max pooling layers reduce the dimension of the input, each of them halving the width and height of the image. The decoder is designed symmetrically: two transposed convolutional layers followed by activation functions. Each of them quadruples the number of pixels, resulting in an output resolution that matches the input.

As we are using RGB images, our input data has three channels (red, green and blue). The first convolutional layer of the encoder increases this to a specified number of features. We consider this number of features a hyperparameter for which we conduct experiments to find a suitable value. However since the number of features influences the size of the linear layer, it is limited by the available GPU memory. To reduce the number of channels back to three in the output, the decoder part also includes a convolutional layer after the two transposed convolutional layers. For the activation function we considered Sigmoid, Tanh, and ReLU (rectified linear unit), but empirical found LeakyReLU to perform best.

Similarly, we also test multiple options for loss functions to be used during model training. This includes standard regression loss functions such as mean squared error (MSE) and mean absolute error (MAE) as well as computer visionspecific ones like structural similarity (SSIM) [50]. We acknowledge that more advanced loss functions such as an identity loss function that reduces the difference in recognized identity rather than the difference in pixel values might also be very suitable in this use-case, but choose to keep this initial general de-anonymization purposely simple to proliferate the usage of our methodology in the future.

6 Techniques

In this section, we introduce all the anonymization and deanonymization techniques that we use in our evaluation. For each, we consider both commonly used basic methods as well as state-of-the-art approaches. We make sure that our selection of methods covers a wide range of categories.

6.1 Anonymizations

For all introduced anonymizations, an example image can be found in Figure 4.

6.1.1 Basics

Basic anonymizations are the most commonly used methods as they are easy to implement and often provide straightforward parameters to control the privacy-utility trade-off.

Eye Mask The pixels in the eye area of the face are removed and replaced by a black bar.

Block Permutation The face image is split into equallysized blocks which are then permuted. The same permutation is used for all images.

Gaussian Noise For every pixel of every channel in the image, random noise is drawn from a Gaussian distribution and added to the pixel's value.

Gaussian Blur The face area of the image is blurred using Gaussian blur. This is done by performing a convolution on the image with a gaussian kernel matrix.

Pixelation The resolution of the image is reduced. The parameter is the number of remaining pixels on either axis.

6.1.2 Adversarial Machine Learning

Anonymization methods in this category achieve their privacy protection by attacking the face recognition machine learning models that are used to identify individuals. These data poising attacks have been criticized as they target specific face recognition models and therefore do not offer any protection anymore when new models get implemented in the future [33]. One example is **Fawkes** [39] which adds "imperceptible pixellevel changes" to face images. Fawkes' use-case assumes that the anonymized images are used to train the recognition system and can therefore "poison" the information base so that later recognition attempts on non-anonymized data fail. The idea is to compute minimal perturbations for an image that cause significant changes in the output of the face recognition model. We use the open-source implementation by Fawkes' authors Shan et al.



Figure 4: Different face anonymization methods we consider

6.1.3 Overlay

k-RTIO [34] (K-randomized transparent image overlays) adds a semi-transparent overlay to the face image. Based on the image's identifier and a secret key, images from a known overlay image data set are selected. The overlay images are then block permuted based on the secret key and combined. This combination is overlayed on the face image. This anonymization is designed to be reversible with the knowledge of the secret key. The use case is the disruption of face recognition systems that may run on cloud hosted images while preserving enough utility so that the anonymized images might still be usable in the cloud environment without the need to download and de-anonymize them.

6.1.4 Differential Privacy

Differential Privacy (DP) is a commonly used framework in state-of-the-art anonymization methods as it allows formal and provable privacy guarantees. By definition, an adversary cannot effectively distinguish between the outputs of a differentially private mechanism. In the case of face anonymization, this would theoretically guarantee that images cannot be reidentified by a face recognition method.

DP Pix [8] The image is first pixelated by averaging the pixels within blocks. Then a Laplace perturbation is added to the pixelized image. The algorithm was originally designed for grayscale images, we adapt it to RGB images by performing all algorithm steps for each channel separately. We implement DP Pix ourselves using the description in [8] and the pseudo-code in [35].

DP Snow [18] A configurable percentage of pixels in the image are replaced with gray pixels. When δ is the percentage of replaced pixels, this anonymization is $(0, \delta)$ -differentially private according to John et al. [18].

DP Samp [35, 49] This method was originally proposed for video anonymization in [49] and adapted for grayscale images in [35]. We further adapt it for RGB images. Our variant works as follows: K-Means is used to generate k clusters from the pixels of the image. For each cluster, the number of pixels within a threshold to the mean cluster color is counted. Based on these frequencies, each cluster is allocated a fraction of the overall privacy budget. The privacy budget of a cluster determines how many pixels within the cluster are randomly sampled. The sampled pixels from all clusters are then used to linearly interpolate the remaining pixels for the final anonymized image. We implemented this ourselves based on the pseudo-code in [35].

6.1.5 *k*-Anonymity

A different formal framework that allows for privacy guarantees is *k*-anonymity. Its basic idea is to modify the data in such a way that any single point is equally likely to belong to any of *k* identities. This allows the preservation of utility and attributes that all *k* identities share while reducing re-identification accuracy to a theoretical maximum of 1/k.

For face anonymization, *k*-anonymity was first formalized and proposed by Newton et al. in [28]. They however make some assumptions that are unsuitable for our use-case (and many real-world scenarios) including that there is only a single image per identity and no other images or identities are added after the initial anonymization [24, 26]. Further, there is no straightforward way to split the anonymized data set into multiple parts without breaking the formal privacy guarantee.

We therefore implement a variation on their approach. We create an anonymization background data set that contains the images of identities which are not used anywhere else in our framework. We train a PCA on the images in this data set and save their representations in a database. When anonymizing an image, we find the k - 1 closest images in the PCA-space (only one per identity). The anonymized image is then the average of the original image and the k - 1 closest images

from the background data set. This allows us to anonymize multiple images for the same person and to later split the anonymized data set into multiple parts without adverse effects. For k-Same-Pixel [28] the k images are averaged in the pixel-space while for k-Same-Eigen [28], the anonymized image is the inverse transform of the average of the k images' PCA representations.

6.1.6 Synthesis

Anonymization methods in this category replace the entire face in the image with a new synthetic one. Since this removes the majority of identifying features of the original face, recognition systems fail to match these images to the correct person. At the same time, utility can be achieved by creating synthetic faces that preserve specific attributes of the original one.

DeepPrivacy [15] Hukkelås et al. use a conditional generative adversarial network which considers original pose and background of the image. It has the goal to preserve a variety of attributes of the original face while protecting the privacy of the individual. We use the authors' open-source implementation.

CIAGAN [23] The approach by Maximov et al., CIAGAN, is based on conditional generative adversarial networks together with a novel identity control discriminator. The goal is to remove identification characteristics of people while keeping the necessary features required for detection, recognition and tracking. Anonymized images are supposed to be high-quality and realistic for human observers. We use the authors' open-source implementation.

6.2 **De-Anonymizations**

In the following, we want to introduce alternative deanonymizations which can be compared to our general deanonymization attacker.

6.2.1 Basics

Basic de-anonymizations are tools from the area of image processing and have not been specifically designed to reverse biometric anonymization methods. However, they can still improve recognition results for a wide range of anonymization methods.

Linear/Bicubic interpolation For pixelation, we simply use linear or bicubic interpolation to upsample the image back to its original size. For any other anonymization, the images are first downsampled and then back up using linear or bicubic interpolation. The intermediate resolution is determined by calculating the SSIM of the re-upsampled image and the original clear image for all images in the deanonymization training data set for a variety of intermediate resolutions. The intermediate resolution that achieves the highest average SSIM is used on the test data set.

Wiener filter [16] This applies a wiener filter to the image. We test both a version where the parameters determined by testing them on the training data set and choosing the ones with highest SSIM and version based on [30] that blindly estimates the parameters for every image individually. We use the implementations from the scikit-image library [48].

Richardson-Lucy Deconvolution [9, 36] This applies a Richardson-Lucy deconvolution on the image. Parameters are blindly estimated on a picture by picture basis using the approach from [9] and the implementation from the scikit-image library [48].

Wavelet denoising [5] This applies the adaptive wavelet thresholding for image denoising approach by Chang et al. as implemented in the scikit-image library [48].

6.2.2 State-of-the-art approaches

Anonymization methods that blur, pixelate or add noise to the image are very similar to processes that naturally happen to images that reduce their quality. Significant amounts of research have been done to mitigate these natural processes which have resulted in deblurring, super resolution and denoising approaches. We can use state-of-the-art approaches from these areas as de-anonymization methods for our artificially degraded images to improve recognition accuracy. We planned to use face specific deblurring approaches such as [40] and [31], however we were unable to get the authors' open-source implementations working.

Deep-Face Super-Resolution [22] This face super resolution approach uses two recurrent neural networks with iterative collaboration for face image recovery and landmark estimation. The goal is to recover high-quality face images from low-resolution images. We use the authors' open-source implementation and abbreviate it as "DIC SR".

Blind deconvolution using a normalized sparsity measure approach [20] Here, a mathematical model is used to reverse blurring on images without any knowledge of the used blurring method. We use the authors' open-source implementation. We often abbreviate this method as "Norm sparsity". **MPRNet** [51] Using a machine learning model with a multi-stage architecture using encoder-decoder pairs in combination with a high-resolution branch that retains local information, MPRNet attempts to restore high-quality images from degraded inputs. The authors provide pre-trained models for denoising and deblurring as well as an open-source implementation that we use.

Stripformer [47] Blurred images are restored using a machine learning model with a transformer-based architecture. We use the authors' open-source implementation as well as the model which they trained on the GoPro dynamic scene deblurring data set by Nah et al. [27].

6.2.3 Specialized approaches

For some anonymization methods, specialized approaches for the exact anonymization that was used can be implemented.

Interpolation For the anonymization DP Snow, we interpolate every completely gray pixel from its eight neighboring pixels while ignoring any neighboring completely gray pixels. Considering the high-resolution property of the used images, this makes the reasonable assumption that neighboring pixels have similar colors and that hard edges are rare in natural face photos.

Learn permutation For (block) permutation, we can use the access to training images with the exact same permutation to learn this permutation and then apply the reverse on the test images. This works by matching the pixel colors from clear to anonymized images.

7 Evaluation

In this section, we evaluate our improved biometric anonymization evaluation methodology. We first present the hypotheses that we want to test and then explain the corresponding experiments and user study and their results.

7.1 Hypotheses

The overall goal of this evaluation is to show that our improved methodology can highlight shortcomings in the privacy protection of biometric anonymization methods better than previous evaluations. This primarily means that we expect our attacker to be more or at least equally successful at identifying individuals in the anonymized data than naive recognition for all anonymization methods (**H1**). For all anonymization methods for which (successful) specialized de-anonymization methods have been proposed, we also expect our de-anonymization to at least partially reverse them which should result in significantly increased success in the identification of individuals for these anonymizations (**H2**). Note, that we do not necessarily expect our general deanonymization to match the specialized ones in the degree of reversal. We expect that our evaluation methodology results in higher accuracies than parrot recognition because our approach is more explicit and specialized for reversibility (**H3**). Also, the face recognition models are trained on clear data which we expect to be more similar to de-anonymized data than anonymized data.

As block permutation does not remove any information from the images, we expect it to be perfectly reversible, meaning that we recover the exact pixel by pixel clear image (H4). Anonymizations based on synthesis override (almost) all identifying information from the image and k-anonymity based approaches average the identifying information from many people in the image. We therefore expect anonymization methods from these two categories to be irreversible by our general attacker (H5). For all other anonymization methods, we expect them to be partially reversible which means that our approach will result in higher accuracies than naive (and parrot) recognition but will not reach the clear data baseline (H6).

We also test the impact of our assumption that training and test data have been anonymized using the exact same anonymization method and parameters. Here, we expect that identification accuracy decreases as parameters get less similar and do not expect de-anonymization to work at all if the anonymization method does not match (**H7**). Finally, we also consider face recognition by humans. We expect our improved methodology to more accurately reflect the human ability to identify people in anonymized images because the human mind instinctively applies de-anonymization methods such as deblurring or interpolation (**H8**).

7.2 Experiments

To test **H1-6**, we perform re-identification experiments. Initially, we generate a baseline by running our experiments without any anonymization or de-anonymization. Then, for every anonymization method which we introduced in the previous section, we test multiple configurations. Like previous evaluation methodologies, we test naive and parrot recognition on the anonymized data without any de-anonymization. We additionally test our improved evaluation methodology, both with any relevant specialized de-anonymizations as well as our general de-anonymization. The de-anonymization methods tested for every anonymization method are shown in Table 2. This table once again highlights that a general de-anonymization method is needed to evaluate anonymization methods because for many anonymizations, no specialized approaches have been proposed.

For **H7**, we also conduct re-identification experiments. We anonymize data using gaussian blur (kernel 29) and deanonymize this data using models trained on images that were anonymized using gaussian blur (kernel 21, 25, 29, 33, 37),

Method	Linear/Bicubic	Wiener Filter	Richardson-Lucy	Wavelet Denoising	DIC SR	Norm Sparsity	Stripformer	MPRNet	Neighbor Interpolation	Learn Permutation	ours	
Eye Mask											1	-
Block Permut.										1	1	
Gauss. Noise	1	1	1	1				✓a			1	
Gauss. Blur	1	1	1			1	1	✓ ^b			1	
Pixelation	1	1			1						1	
Fawkes	1	1	1	1				✓a			1	
DP Pix	1	1	1					✓a			1	
DP Snow	1	1	1	1				✓a	1		1	
DP Samp											1	
k-Same-Pixel											1	
k-Same-Eigen											1	
DeepPrivacy											1	
CIAGAN											1	
k-RTIO											1	
^a Denoising ^b Deb	lurriı	ng										

Table 2: Combinations of anonymization and deanonymization methods evaluated

gaussian noise (sigma 200), DP Snow or pixelation (size 16).

For **H8**, we perform a user-study which is described in the next subsection.

7.3 User-Study

We conduct a user-study to evaluate whether our improved evaluation methodology better represents a human's ability to identify individuals in anonymized face images. While it would be straightforward to let humans conduct the same re-identification experiments as we perform with machine learning face recognition methods, this is not feasible because of the large number of images in the enrollment set (ca. 6000). We therefore opt to let participants decide whether two face images, one of which is anonymized, show the same person. The rationale is that if a participant is not able to recognize that two images belong to the same person, the anonymization method was successful at protecting this person's identity.

To reduce the scope of the study, we do not test anonymizations that are very similar to others while making sure to include an anonymization method from every category. For each anonymization method, we randomly choose 8 pairs of images of which 4 pairs show women and 4 pairs show men¹ and of which 4 pairs show the same person in both images and 4 do not. For each pair of images, we ask participants (n=98; minimum number of votes per image pair=34) whether both images show the same person and they can answer 'yes', 'no' or 'not sure'. We measure the percentage of 'yes' votes on the four matching image pairs for every anonymization.

Ethical Considerations: We obtained approval for this experiment from the ethics commission of the Karlsruhe Institute of Technology (research project "Evaluierung von Gesichtsanonymisierungen"). The survey data was collected in anonymized form.

7.4 Data sets

We use a subset of the commonly used CelebA data set [21] as the base set for our experiments. We create our subset by sorting the identities in CelebA by their number of images and choose the top 5000 identities. This is done because for the re-identification experiments, more images per identity is preferential to allow for successful matching and to reduce the impact of outliers. From those 5000 identities, we randomly choose 200 for our anonymization background set and 4800 for the evaluation data set of which 300 are for the test set and the remaining 4500 identities are used for de-anonymization training.

Before our experiments, we run all images of our CelebA subset through a pre-processing pipeline. Detecting a face bounding box is a first processing step of the majority of facespecific anonymization and de-anonymization methods and is usually performed by a state-of-the-art face detection algorithm that is not directly part of the actual (de-)anonymization method. Therefore, to improve performance and to remove any effects that degraded face detection on anonymized images may have on our results, we perform this face detection step once and then disable it whenever possible in subsequent methods.

Our pre-processing is based on the pipeline of LightFace [38] and works as follows: We use RetinaFace [7] to detect the bounding box of any faces in the images. Note, that we do not use the bounding boxes provided by CelebA as we found them to be inaccurate at times and in order to resemble a standard face recognition pipeline more closely. We choose the face with the largest bounding box that is fully in the image and crop the image to the smallest square that fully includes the face when rotated so that both eyes are on a horizontal line above the nose. These images are then resized to a resolution of 224x224 pixels which is the standard input size for LightFace.

7.5 Evaluation Framework

In order to run our experiments, we implemented an evaluation framework (Figure 5 contains an overview of the design) that allows us to run the different experiments described above. In a first step, the framework creates an anonymized copy of the evaluation data set which in our case is the subset of CelebA which was already pre-processed minus the anonymization background set. Afterwards, evaluation and

¹as determined by the CelebA attributes



Figure 5: Design of our evaluation framework

anonymized data set are used to create the training data set for the de-anonymization, the enrollment data set and the test data set. The test data set is then de-anonymized using the configurable de-anonymization method which was trained using the training data set. Finally, state-of-the-art face recognition methods are used with the enrollment data set and the de-anonymized test data set and those results are used to calculate a variety of metrics. Because we have no clear indication which face recognition model may work the best on (de-) anonymized data, we test multiple. We use pre-trained models of multiple state-of-the-art recognition models which are integrated into the LightFace framework: Facenet [37], VGGFace2 [3], ArcFace [6] and Dlib [19]. Additionally, we used a combination of the face recognition model (fr-knn) [10] which uses a pre-trained feature extractor based on [19] and then classifiers using k-nearest neighbours. The framework was implemented in python (version 3.8) using the numpy (version 1.19.5) and scikit-learn (version 1.0.1) libraries.

7.6 Metrics

Our main metrics are the accuracies of different face recognition models when performing re-identification experiments. In addition to re-identification experiments, we also compare the images of the test data set with their corresponding clear image. This comparison is measured using SSIM [50]. We measure SSIM for all images in the test data set and report mean and standard deviation. While this is not the main goal of de-anonymization, it is a commonly used general metric in image manipulation.

7.7 Parameters

Hyperparameter search We conduct a hyperparameter search for our general de-anonymization method by running

a variety of configurations testing de-anonymization performance on a data set anonymized using gaussian blur (kernel 29). For each considered hyperparameter, we test multiple options and choose the one that results in the best performance in this experiment. We choose LeakyReLU as our activation function, SSIM as our loss function, an initial learning rate of 0.0001 and a batch size of 64. We were able to further improve results by adding a reduce-on-plateau learning rate adaption to our training that multiplies the current learning rate by 0.75 if the validation loss does not improve for five epochs. We train for a maximum of 200 epochs but stop early when we don't measure an improvement in validation loss for 20 epochs.

Anonymization parameters Most anonymization methods can be configured using parameters that determine their privacy-utility trade-off. We choose these parameters based on common choices in related work or (if applicable) the method's author's recommendation. We strive to evaluate the anonymizations on a realistic privacy-utility trade-off. The specific parameters for each anonymization method are included in the appendix (Table 4).

7.8 Results

Not broken	Partially Reversible	Highly Reversible
k-Same-Pixel	Eye Masking	Block permutation
k-Same-Eigen	Pixelation	Gaussian Noise
DeepPrivacy	DP Pix	Gaussian Blur
CIAGAN	DP Samp	Fawkes
		DP Snow
		k-RTIO

Table 3: Overall success of our general de-anonymization

Example images that were de-anonymized using our approach can be found in Figure 6. An overview over the results for naive and parrot recognition, our approach and our user study can be found in Figure 7. This plot includes the results for the different experiments for all anonymization techniques. Generally, a high value indicates that experiment showed that the images still contained enough personal information to identify an individual. Therefore a successful anonymization would result in low values for all experiments. For naive and parrot recognition as well as our approach, the best performing recognition model is shown each, which matches our strong attacker model. We find that for many anonymization methods accuracies exceeding 50% can be measured and that for most anonymization methods, our approach results in significantly higher values than the other experiments.

This section also includes plots for the anonymizations Block permutation (Figure 8), Gaussian Blur (Figure 9), DP Pix (Figure 10) and Pixelation (Figure 11). Plots with all de-anonymization methods as well as plots for all other





DP Samp







Figure 6: De-anonymized images for different anonymization methods



Figure 7: Results Overview



Figure 8: Evaluation result for Block Permutation



Figure 9: Evaluation result for Gaussian Blur (kernel 29)

anonymization methods can be found in the appendix. In these plots, different de-anonymization methods are compared against the baseline of clear data as well as naive and parrot recognition on the anonymized data. High differences between naive or parrot recognition and a de-anonymization method indicate that this technique was able to reverse the

anonymization method and to re-create an image on which face recognition methods were able to identify an individual. For block permutation, we find that the specialized learn permutation de-anonymization is able reach clear level performance with our general approach not much lower. While the specialized approaches for gaussian blur are able to increase



Figure 10: Evaluation result for DP Pix



Figure 11: Evaluation result for Pixelation (size 16)

re-identification accuracies over naive and parrot level, they are below our general approach which itself also does not reach clear level. Similar scenarios can be seen for DP Pix and Pixelation.

In Figure 12, the effects of the training data not exactly matching the testing data can be seen. In all cases, the test data was anonymized using Gaussian Blur (kernel 29), our general de-anonymization was however trained with data that was anonymized using other anonymizations. We find that the best result is achieved when training and testing data match and the performance decreases as the two data sets get less similar.

We can obverse **H1** and **H3** to be true for most anonymization methods. Our approach achieves significantly higher accuracies and SSIMs than naive and parrot recognition for many anonymization methods. However, there are some exceptions in which parrot recognition performs better than our approach and even naive recognition is within a small margin, namely Eye Masking, DeepPrivacy, CIAGAN and *k*-Same-Eigen. All these anoymizations share that they remove large parts of the face and the only option for a de-anonymization therefore is to reconstruct these areas using the general structure of faces. We see this as an indication that no information





Figure 12: Comparison of different training data sets

is better for the face recognition than (incorrect) reconstructed information.

Our experiments included specialized de-anonymization methods for the anonymization methods block permutation (Figure 8), gaussian blur (Figure 9), gaussian noise (Figure 17), pixelation (Figure 11) and DP Pix (Figure 10). In these cases we find that a) the specialized de-anonymization methods result in higher re-identification accuracies and b) our general approach can also significantly increase re-identification, thereby confirming hypothesis **H2**.

For **H4**, we find that block permutation can be perfectly reversed using our specialized de-anonymization that learns the permutation and our general machine learning approach is able to match this re-identification accuracy, see Figure 8. At the same time, SSIM for our approach is below 1.0. This however can be expected considering our attacker uses convolutional layers which are bound to loose some information.

For none of the anonymization methods in the categories synthesis and *k*-Anonymity does any re-identification accuracy of our approach exceed 15%, see Figure 7, see DeepPrivacy (Figure 23), CIAGAN (Figure 24), *k*-Same-Pixel (Figure 16) and *k*-Same-Eigen (Figure 22). This confirms **H5**.

For all other anonymization methods, we find as predicted in **H6** that we are able to partially reverse them and thereby increase re-identification and similarity metrics. We do find that the level of de-anonymization varies significantly between anonymization methods from close to perfect for DP Pix (Figure 10) to very little improvement in DP Samp (Figure 15). We therefore make an additional distinction in our categorization between partially reversible and highly reversible anonymizations based on whether the average re-identification accuracy of our approach is closer to that of anonymized data or clear data. A categorization of all tested anonymization methods based on whether our general de-anonymization method was able to break them is shown in Table 3.

The results of the experiment comparing different training data sets for our general attacker on the de-anonymization of gaussian blur can be found in Figure 12 and show **H7** to be true.

When considering the results of our user study in Figure 7, we find that generally, the results match those measured in the alternative approaches. However, most often, the user study is close to the accuracy of parrot recognition which is often outperformed by our approach. This means that even when humans are unable to identify individuals in anonymized face images, our approach often still can. This is particularly apparent for block permutation where de-anonymization relies heavily on inversion. Therefore, our approach performs even better than expected in **H8**.

8 Limitations

While we consider the simplicity of the machine learning model's design of our general de-anonymization to be a feature which allows easier usage of our evaluation methodology, we acknowledge that a more advanced model might result in even better de-anonymization results. Improvements like this may include further tuning of hyperparameters, longer training with more data or improvements to the data preprocessing. Further, we consider that SSIM as a loss function does not ideally capture our goal which is the reconstruction of the identity in the image, not the pixel values. Therefore an identity loss function rather than a image similarity loss function like SSIM could be more suitable. In this line of thought, using a generative adversarial network (GAN) with our current model as the generative network might also improve performance.

We acknowledge that our user-study could be improved by collecting more data. Both more participants and more samples per anonymization method could be used to further increase confidence in our results. In the current form, the random choice of images per anonymization leads to high variances when the identity decision is already difficult on clear images.

9 Conclusion and Future Work

There are significant privacy risks associated with the collection of biometric data which facilitates the requirement for anonymization methods. Current state-of-the-art evaluation of anonymization methods assumes a weak attacker model and does not consider the reversal of the anonymization. At the same time, strong attackers for specific anonymization methods have been shown to be successful. In this work, we propose an improved evaluation methodology with an explicitly stronger attacker model that considers de-anonymization methods. We provide a general face deanonymization method using deep learning that can be used to evaluate any face anonymization method. Finally, we test our methodology with a multitude of different face anonymization methods.

We find that a majority of anonymization methods is at least

partially reversible and therefore protects the privacy of individuals less than previously thought. This highlights the need for strong attacker models in the evaluation of anonymization methods. Our general de-anonymization method is able to successfully reconstruct anonymized images in 10 out of 14 cases. While it is not always able to match the performance of specific de-anonymizations, it always gives an indication of a anonymization method's reversibility.

Future work in this area may include applying our improved evaluation methodology to other anonymization methods, other recognition methods and other biometric traits.

In conclusion, we find that although irreversibility is a core property of any anonymization method, many are not actually irreversible. This also highlights how the current evaluation methodology of anonymization methods is flawed as reversal attacks are not considered. In this work, we have shown how important such experiments are because we show that many anonymization methods can be at least partially reversed and are therefore less privacy protecting as previously thought.

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Appendix

9.1 Anonymization parameters

Table 4 shows the used parameters for all anonymization methods. Methods that do not have any configurable parameters are excluded.

Method	Parameters
Permutation	block size 32
Gauss. Noise	σ 200
Gauss. Blur	kernel size 29
Pixelation	size 16
Fawkes	mode high
DP Pix	ε5, b12, m16
DP Snow	δ 0.5
DP Samp	ε 25, k 24, m 12
k-Same-Pixel	k 10
k-Same-Eigen	k 10

Table 4: Parameters of anonymization methods

9.2 Full Results

This section includes the results of all experiments that we run in the context of this work. See Figure 13 for eye masking, Figure 14 for pixelation, Figure 15 for DP Samp, Figure 16 for *k*-Same-Pixel, Figure 22 for *k*-Same-Eigen, Figure 17 for gaussian noise, Figure 18 for gaussian blur, Figure 19 for Fawkes, Figure 20 for DP Pix, Figure 21 for DP Snow, Figure 23 for DeepPrivacy, Figure 24 for CIAGAN and Figure 25 for k-RTIO.



Figure 13: Evaluation result for Eye Masking



Figure 14: Evaluation result for Pixelation



Figure 15: Evaluation result for DP Samp



Figure 16: Evaluation result for k-Same-Pixel



Figure 17: Evaluation result for Gaussian Noise



Figure 18: Evaluation result for Gaussian Blur



Figure 19: Evaluation result for Fawkes



Figure 20: Evaluation result for DP Pix



Figure 21: Evaluation result for DP Snow



Figure 22: Evaluation result for *k*-Same-Eigen



Figure 23: Evaluation result for DeepPrivacy





Figure 24: Evaluation result for CIAGAN