Implicit Pairs for Boosting Unpaired Image-to-Image Translation

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Abstract

In image-to-image translation the goal is to learn a mapping from one image domain to another. Supervised approaches learn the mapping from paired samples. However, collecting large sets of image pairs is often prohibitively expensive or infeasible. In our work, we show that even training on the pairs implicitly, boosts the performance of unsupervised techniques by over 14% across several measurements. We illustrate that the injection of implicit pairs into unpaired sets strengthens the mapping between the two domains and improves the compatibility of their distributions. Furthermore, we show that for this purpose the implicit pairs can be pseudo-pairs, i.e., paired samples which only approximate a real pair. We demonstrate the effect of the approximated implicit samples on image-to-image translation problems, where such pseudo-pairs can be synthesized in one direction, but not in the other. We further show that pseudo-pairs are significantly more effective as implicit pairs in an unpaired setting, than directly using them explicitly in a paired setting.

1. Introduction

The goal of image-to-image translation is to learn a mapping from one image domain to another. In recent years, a plethora of methods has arisen to solve the problem using deep neural networks. A straightforward supervised approach is to learn the mapping from paired samples [11]. However, collecting large sets of image pairs is often prohibitively expensive or infeasible. Learning the mapping from unpaired data is thus more attractive, but significantly more technically challenging, as the problem becomes highly under-constrained. A common solution is to limit the space of possible mappings to those that obey circularity constraints [29, 28, 14].

Bridging the gap between paired and unpaired training, Tripathy et al. [21] propose a hybrid framework that simultaneously considers paired and unpaired image samples. In their work, they demonstrate that training explicitly on the paired samples yields a boost in performance compared to unsupervised techniques, which utilize only unpaired samples. In our work, we argue that even training on the pairs implicitly, boosts the performance of unsupervised techniques. An implicit pair is a pair that exists in the training data, but is not used directly in the loss computation. Through extensive experiments we analyze in this paper the power of implicit pairs in an unpaired setting. Furthermore, we demonstrate that for this purpose, the implicit pairs can be pseudo-pairs, i.e., paired samples which only approximate a real pair and that implicit pseudo-pairs still boost the performance of learning in an unpaired setting.

This study examines the strength of the implicit pseudo-pairs in an asymmetric setting. In this setting there is a process, or model, which allows estimation of the mapping from one domain to the other, but not in the opposite direction. Consider, for example, the domains wearing eyeglasses and not wearing eyeglasses which capture facial images where the subjects are distinguished by whether or not they are wearing eyeglasses. While a mapping from not wearing eyeglasses to wearing eyeglasses may be easy to approximate using a simple model-based synthesis technique, the inverse mapping does not have a simple model-driven solution.

We start the analysis by showing that the quality of the mappings learned depends on the portion of implicit pairs in the dataset. This non-intuitive finding encourages the exploration of using pseudo-pairs as implicit pairs in an unpaired setting. We demonstrate the effect of the approximated samples on image-to-image translation problems. We further show that pseudo-pairs are significantly more effective as implicit pairs in an unpaired setting, than using them explicitly in a paired setting. Explicitly stated, our contributions are:

- We demonstrate that image-to-image translation net-
works benefit from the latent signal that implicit pairs add to the dataset.

- We analyze the effect of the percentage of pairs in the dataset and demonstrate that even a small percentage allows for better datasets that reach performance rates close to that of fully paired datasets.

- We introduce pseudo-pairs to the image-to-image translation framework and show that pseudo-pairs are more effective in an unpaired setting than as explicit pairs in a paired setting.

2. Related Works

Pix2Pix [11] was the first successful attempt to use a conditional GAN to learn a mapping between two image distributions. As a supervised method it requires paired samples, one from each distribution, to be explicitly linked in the training phase.

As gathering a large paired dataset can be difficult and expensive, unsupervised architectures were suggested which do not require such explicit pairing [29, 17, 28, 14, 6].

Bridging the difference between supervised and unsupervised architectures, several methods allow the use of a small set of paired images, together with a large set of unpaired ones in a semi-supervised fashion. They accomplish this by alternating between supervised and unsupervised phases during training [12, 21]. Other semi-supervised solutions separate the learning of the joint distribution and the marginal distribution of the domains, by independently learning the from the supervised set and the unsupervised set [9, 16].

Deep neural networks require large amounts of data to train properly, which can prove prohibitively expensive in some cases. To cope with this problem various methods have been devised to create more samples by augmenting existing data into new samples in order to create meaningful expressions of the underlying distribution. Simple augmentation methods for images include rotation, skewing, cropping and other affine transformations. These simple methods are quite ubiquitous, but limited in the amount of data they can generate, as well as the amount of effective information that they add to the dataset.

Other more complex augmentation methods could be model-based, use learned generative models and even GANs [24, 5, 22, 3, 26, 8, 19, 20].

Lastly, we are not aware of any prior work that use more advanced methods to augment a dataset that is used to train a GAN. This leaves this field restricted in ways that other ML domains are not.

3. Background and Outline

3.1. Paired and unpaired settings

Modern image-to-image translation models use GANs to obtain plausible images in the target domain. When using only an adversarial loss the translation problem is highly under-constrained. Thus, it could easily lead to mode collapse where the generator learns to fool the discriminator by producing images only from a small part of the target distribution.

Algorithm 1 Learning in Paired Setting

| Input: A paired dataset $(A, B)$.
| Output: $G_{AB}$ and $G_{BA}$.
| for each epoch do
| Sample pairs $(a, b) \in \{A, B\}$
| Update model in respect to:
| $L(G_{AB}, G_{BA}, D_A, D_B, a, b)$
| end for

Algorithm 2 Learning in Unpaired Setting

| Input: An unpaired dataset $(A, B)$.
| Output: $G_{AB}$ and $G_{BA}$.
| for each epoch do
| Sample $a \in A, b \in B$
| Update model in respect to:
| $L_{AB}(G_{AB}, G_{BA}, D_B, a)$
| $+L_{BA}(G_{AB}, G_{BA}, D_A, b)$
| end for

To constrain the problem, the model can be trained using pairs, which are explicitly provided during training. Algorithm 1 describes a high-level overview of a learning algorithm in a paired setting, where the pairs are explicitly used in the loss function $L$. In general, explicit-pairs constraints alleviate most of the problems of mode collapse. Learning with explicit pairs constitutes the paired setting.

A notable example for an algorithm that uses explicit pairs is the Pix2Pix framework [11] which conditions the discriminator and the generator on the given source and target pairs. More formally the algorithm samples pairs $(a, b) \in \{A, B\}$ and trains the generator and discriminator with the following adversarial loss function:

$$L_{CGAN}(G_{AB}, D_B) = \mathbb{E}_{a,b}[\log D_B(a, b)] + \mathbb{E}_a[\log(1 - D_B(a, G_{AB}(a))],$$

where $G_{AB}, D_B$ are the generator and discriminator, respectively. Pix2Pix uses the pairs to further constrain the mapping with an $L1$ distance loss which requires the generated samples to be close to the ground-truth paired sample:

$$L_{L1}(G_{AB}) = \mathbb{E}_{a, b}[||y - G_{AB}(a)||_1].$$
The complete loss function in the $A \rightarrow B$ direction is the combination of these functions:

$$L = L_{cGAN} + L_{L1}$$

There are many cases where it is difficult or even impossible to have paired samples. In such cases, the translation can be learned in an unpaired setting. In the unpaired setting there are two training sets, one for each domain, but the instances in the two domains are not explicitly related. They may contain pairs but in such a case their correspondence is not given, and therefore is not used in the loss function. See Algorithm 2, where the translation functions $G_{AB}$ and $G_{BA}$ are trained using instances from $A$ and $B$, but no pair is explicitly used even if the training sets contains such pairs.

Various solutions have been proposed to better constrain the mapping in the severely unconstrained unpaired setting. For example, in CycleGAN and DualGAN [29, 28] the adversarial loss is combined with a cycle consistency loss.

$$L = \alpha L_{cGAN}(G_{AB}, G_{BA}) + \lambda L_{cycle}(G_{AB}, G_{BA})$$

where the adversarial objective used to encourage plausible generated images in the target domain is:

$$L_{cGAN}(G_{AB}, G_{BA}) = \mathbb{E}_{b \sim p_{data}(b)}[\log D_B(b)] + \mathbb{E}_{a \sim p_{data}(a)}[\log(1 - D_B(G_{AB}(a)))]$$

and the cycle consistency loss is defined according to:

$$L_{cycle}(G_{AB}, G_{BA}) = \mathbb{E}_{a \sim p_{data}(a)}[\|G_{BA}(G_{AB}(a)) - a\|_1] + \mathbb{E}_{b \sim p_{data}(b)}[\|G_{AB}(G_{BA}(b)) - b\|_1]$$

It should be stressed that the above algorithm does not use pairing information even if the training set consists entirely or partially of pairs.

### 3.2. Implicit pairs

The unpaired framework does not explicitly use any mutual information of paired data, which may exist in the unpaired sets. We argue that having paired data still boosts the translation learning performance, as the pairs implicitly guide the learning. In our experiments, we define $\alpha$-paired datasets, which are datasets in which an $\alpha$ portion of the dataset is paired. For example, with $\alpha = 0.25$, a quarter of the samples are paired and the rest are unpaired.

In the paired setting it is assumed that $\alpha = 1$ and $|A| = |B|$. While prior work ignored the possible existence of pairs, we consider and analyze the effect of having implicit pairs. Technically, we learn the mapping functions $G_{AB}$ and $G_{BA}$ using $\alpha$-paired datasets in an unpaired setting, where the learning process is completely unaware to the implicit pairs.

In Section 4.1, we analyze the performance of learning from implicit pairs, and show that a mix of unpaired and paired samples perform better in an unpaired setting.

**Implicit pseudo-pairs.** As discussed above, there are many situations where obtaining pairs is hard. However, in some cases, pseudo-pairs can be synthesized, see for example Figure 1. The question is whether these imperfect pairs, which only approximate real pairs, can be used as effective implicit pairs. To answer this question, we extend our $\alpha$-paired datasets to $\alpha$-pseudo-paired dataset where the pairing is carried out between generated pseudo-samples in domain $A$ and real samples in domain $B$. With implicit pseudo-pairs, the learning procedure still follows Algorithm 2.

To augment the data, we assume we are provided with a model $M(b) \approx a$ that takes samples $b \in B$ and generates samples that approximate samples $a \in A$. The model $M(b)$ can be interpreted as a simplification of the latent function $G_{BA}$. See Figure 1 for an illustration of pseudo-pairs in different datasets.

Figure 2 provides an overview of our approach in this setting. Given an unpaired dataset, we construct an $\alpha$-pseudo-paired dataset using a model $M(b)$ to inject pseudo-samples to the unpaired sets. Note that in this asymmetric problem, where a model $M(b)$ exists, the inverse mapping is of greater interest (as we can use $M(b)$ to obtain analogous samples in domain $A$).

In the following section, we report on experiments that show that implicit pseudo-pairs boost the performance in the unpaired setting, and that using them as explicit pairs in a paired setting is significantly less effective.

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**Figure 1. illustration of pseudo-pairs.** (a) Pseudo-smiling and neutral faces (b) Pseudo-eyeglasses and faces without eyeglasses.
Figure 2. Learning with implicit pseudo-pairs. Given a model $M(b)$, we generate approximations of samples in domain $B$ and augment them to domain $A$.

Table 1. Reconstruction loss for over several pairing ratios, lower is better. A2B is photo $\rightarrow$ labels, B2A is labels $\rightarrow$ photo.

| $\alpha$ | Cityscapes | CVC − 14 | Facades |
|---|---|---|---|
| 0 (unpaired) | 0.26 0.22 | 0.23 0.24 | 0.36 0.84 |
| 0.25 | **0.24** 0.21 | 0.28 0.29 | **0.33** 0.84 |
| 0.5 | **0.24** 0.22 | **0.22** 0.23 | 0.37 **0.80** |
| 0.75 | 0.27 0.22 | 0.24 **0.22** | 0.37 0.84 |
| 1 (paired) | 0.25 0.22 | 0.23 0.25 | **0.33** 0.87 |

Table 2. FCN-scores for different implicit pairing ratios, $\alpha$ on Cityscapes labels $\rightarrow$ photo, higher is better. Remarkably there is not a single instance where complete pairing is the best option.

| $\alpha$ | Per-pixel acc. | Per-class acc. | Class IOU |
|---|---|---|---|
| 0 | 0.46 | 0.09 | 0.07 |
| 0.25 | **0.69** | **0.20** | **0.15** |
| 0.5 | 0.69 | 0.18 | 0.14 |
| 0.75 | 0.55 | 0.17 | 0.13 |
| 1 | 0.65 | **0.20** | **0.15** |

Table 3. FCN-scores for different implicit pairing ratios, $\alpha$ on Cityscapes photo $\rightarrow$ labels, higher is better. Remarkably there is not a single instance where complete pairing is the best option.

| $\alpha$ | Per-pixel acc. | Per-class acc. | Class IOU |
|---|---|---|---|
| 0 | 0.571 | 0.132 | 0.100 |
| 0.25 | 0.657 | 0.138 | 0.108 |
| 0.5 | **0.663** | **0.142** | **0.111** |
| 0.75 | 0.582 | 0.141 | 0.108 |
| 1 | 0.658 | 0.141 | 0.110 |

4. Experiments and Results

4.1. The Power of Implicit Pairs

To validate our hypothesis that implicit pairs positively affect the result of training in the unpaired setting, we train a dual generator-discriminator architecture (CycleGAN) on $\alpha$-paired datasets composed of various image datasets. Specifically, we use the following paired datasets: Cityscapes [7], Facades [23] and the CVC-14 [10] datasets, split the datasets into train and test sets and sample the train sets to generate various $\alpha$-paired dataset configurations. In all our experiments, we select $|A| = |B|$ samples to generate balanced datasets.

To evaluate the performance on the test set, we measure the MSE between the generated images and their true counterparts. Additionally we use the FCN-score metric introduced in [11] to evaluate the learned translations for the Cityscapes [7] dataset. Please refer to the supplementary material for more information regarding the evaluation metric and its use.

We perform a set of experiments on $\alpha$-paired datasets in an unpaired setting. To learn the translation mappings, we train a vanilla CycleGAN network [29]. Please refer to the supplementary material for additional information regarding the architecture and parameters used. We report our evaluation in Tables 1, 3, 2. As can be expected, 1-paired datasets generally yield better performance than 0-paired datasets with an average improvement of 14.2%. More interesting is the fact that having even a few paired samples improves the results dramatically. Remarkably it seems that in most cases using a completely paired dataset is not the best option. Instead using a mix of paired and unpaired samples is usually a better strategy, surpassing completely paired datasets on average by 3.4%. In Figure 3, we illustrate a random sample from the Cityscapes dataset and its results given different training dataset configurations. Refer to supplementary material for more results.
4.2. Pseudo-Pairs for Implicit Learning

In the previous section, we demonstrated that implicit pairs positively affect the results of image-to-image translation problems. However, in most cases, it is difficult, or unreasonable, to obtain such paired samples. Therefore, we explore a more challenging, yet applicable, setting where the pairs do not originate from real samples. In this setting, we assume we are provided with a model $M(b)$, as described in Section 3.2, that generates samples which approximate samples in the analogous domain $A$.

Our approach is to generate, for each sample in domain $B$, a paired pseudo-sample using $M(b)$ and use it to augment the samples in domain $A$. This approach creates pseudo-paired datasets with a 50% pairing ratio. An overview of this method is shown in Figure 2.

For the experiments on pseudo-pairs, we use the CelebA dataset. We generate two different types of pseudo-α-paired datasets on which we evaluate our method on (i) faces with and without eyeglasses and (ii) smiling and neutral faces. The datasets can be obtained using the labeling information available for each image in the CelebA dataset. In (i), we generate pseudo-samples with eyeglasses using simple heuristics. As the facial landmarks are available, we generate ellipses around the eyes by sampling a random height $h$ in the range of $[10, 25]$ pixels, a random width in the range of $[h/2, 2 \cdot h]$ and a transparency coefficient in the range $[0.1, 1.0]$. The two ellipses are connected by a line with the same transparency and with width in the range of $[h/5, h/2]$. In (ii), we use the technique of Averbuch et al. [4] to generate smiling pseudo-samples. It is important to note that in both cases, it is significantly more challenging to generate clean samples in the inverse direction. See Figure 1 for an illustration of pseudo-pairs in both types of datasets.

Assessing the quality of trained GANs is difficult. One of the reasons for this is that they can accomplish their prescribed goals in ways that defy the expected behavior. For example, when learning to remove eyeglasses, the model could learn to replace the face with another face that is not wearing eyeglasses instead of learning the intended translation. To measure robustness against learning non-meaningful mappings, we would like to measure how successful the mapping is in retaining the expressiveness of the original sample which is not correlated to the task at hand.

Following previous works that use the MSE in representation space as either a perceptual or an identity loss term [27, 2, 15, 13, 25], we use a representation-space similarity measure, InfoSim, to measure the preservation of information not related to the task between the input sample and its generated counterpart. In the case of facial modification tasks, we would like to measure how well the facial identity is preserved after the modification. For that end, we use the representations learned by the OpenFace network [1]. The network is trained for facial recognition and is therefore invariant to transient features, such as smiling or wearing eyeglasses. To measure the similarity we use the MSE between the representation of the input and output images.

Pseudo-pairs experimental setup. In our experiments, we sample $|A| = |B| = 2k$ unpaired samples from CelebA [18]. The resolution of the images is 64X64. Unless stated otherwise, all of the experiments were done using the CycleGAN model described above.

All of the augmentations are done by adding samples to domain A. The qualitative results shown in the following experiments were sampled randomly from the test set and used throughout our experiments for consistency. More results can be found in the supplementary material.

Comparing implicit pseudo-pairs to baseline methods. We evaluate our pseudo-pairs augmentation technique against three augmentation baselines: (i) no-augmentation, (ii) pseudo-unpaired augmentation and (iii) natural augmentation of real images belonging to the corresponding domain. In (i), we do not augment the basic dataset configuration with any samples. In (ii), we augment the basic dataset configuration with pseudo-samples whose paired real samples are not in the dataset. In (iii), we simply augment the basic dataset configuration with more real images, sampled from the full dataset.

The InfoSim results for the baseline methods are reported in Table 4. Figures 4, 5 demonstrate the results of these experiments. As the results illustrate, using implicit pseudo-pairs improves the quality of the translation while better preserving the facial identity. For instance, it is especially noticeable that using implicit pseudo-pairs introduces fewer artifacts in comparison to the other approaches.

| Task                | ours    | (i)       | (ii)      | (iii)     |
|---------------------|---------|-----------|-----------|-----------|
| Smile removal       | 0.00207 | 0.00357   | 0.00329   | 0.00344   |
| Eyeglass removal    | 0.00283 | 0.00495   | 0.00418   | 0.00467   |

Table 4. InfoSim comparison with the baseline augmentation methods described in Subsection 4.2. Lower is better.

Pseudo-pairs ratio analysis. In Section 4.1, we demonstrated that having different ratios of pairs in the dataset can have a significant effect on the results. Here we continue this line of inquiry by evaluating the effect different ratios of pseudo-pairs have. We test the following α-paired configurations: $\alpha = 0.25, 0.5, 0.9, 1.0$. To create a $\alpha = 0.25$ pseudo-paired dataset, half of the augmentation samples are paired and the other half are unpaired. To create datasets with a pairing ratio higher than 50% we have to reduce the number of real samples in domain A. To do
so, we sub-sample the real domain A samples, in the 0.5-pseudo-paired dataset. For the 0.9-pseudo-paired dataset we sub-sample 200 real samples from domain A and for the 1-pseudo-paired dataset we remove all of the real samples in domain A. The InfoSim results for these experiments are reported in Table 5. The results clearly demonstrate that the more pairs we have in the dataset, the better the identity is preserved. The qualitative results for these experiments are demonstrated in Figure 6. As the figure illustrates, although having more pairs allows us to better preserve the facial identity, it also reduces the ability of the model to learn the task itself. We propose that this occurs because as the model is exposed to more pseudo-pairs it is also exposed to fewer examples of the real domain and thus is less able to generalize to the real task. This is especially pronounced in the smile removal task as the generation model $M(b)$ is based on a closed set of smile templates and generalizing from that limited set is hard.

**Pseudo-pairs in different image-to-image translation settings.** In previous experiments we have used the generated pseudo-pairs in an implicit fashion. To understand more fully the effect the pairs have on training of models we further experiment with using them in explicit and semi-explicit settings. For explicit training we use the previously mentioned Pix2Pix model [11] and for semi-explicit learning we use the approach suggested by Tripathy et al. [21]. The explicit and implicit experiments are trained with the 1-pseudo-paired dataset. The semi-explicit experiment is trained with a 0.5-pseudo-paired dataset with the paired samples used explicitly and the unpaired samples used implicitly. From the InfoSim numbers in Table 6 and the qualitative results in Figure 7 it is clear that both of these approaches are inferior to the implicit approach. Comparing the results of the explicit Pix2Pix experiment with that of the implicit CycleGAN experiment in Figure 6 it is clear that although both experiments are equal in every other re-

| Source | baseline | +natural | +unpaired | +paired |
|--------|----------|----------|-----------|---------|

**Figure 4.** Eyeglass removal results using different dataset configurations. Above we illustrate our randomly selected results (on the right) compared against three augmentation baselines, described in Section 4.2.

**Figure 5.** Results for the smile removal task using different dataset configurations. Above we illustrate our randomly selected results (on the right) compared against three augmentation baselines, described in Section 4.2.

**Table 5.** InfoSim values for pairing ratios experiments on the smile removal task. Lower is better.

| Pairing Ratio | 0.25-Paired | 0.5-Paired | 0.9-Paired | 1-Paired |
|---------------|-------------|------------|------------|---------|
| InfoSim       | 0.00248     | 0.00207    | 0.00102    | 0.0073  |

**Figure 6.** Pseudo-pair ratio analysis for the smile removal task. Above we illustrate a few randomly selected results using various pairing ratios. As the figure illustrates, using a 50% pairing configuration yields identity-preserving results which perform the task (smile removal in this case) better than a higher pairing ratio.
Table 6. InfoSim values for explicit, semi-explicit and implicit experiments on the smile removal task. Lower is better.

|          | Implicit | Explicit | Semi-explicit |
|----------|----------|----------|---------------|
|          | 0.00207  | 0.00259  | 0.00313       |

Table 7. InfoSim values for scalability experiments on the eyeglass removal task. Lower is better.

|          | Implicit Paired | Implicit Unpaired | No Augmentation |
|----------|-----------------|-------------------|-----------------|
|          | 0.00223         | 0.00319           | 0.00432         |

Figure 7. Smile removal with pseudo-pairs in different settings. Above we illustrate a few randomly selected results by models trained using either an explicit ([11]), semi-explicit ([21]), or implicit ([29]) settings. As the figure illustrates, an implicit setting leads to the best and most consistent results.

Figure 8. Scalability experiments on the eyeglass removal task. Above we illustrate our randomly selected results (on the right) compared against two augmentation baselines, when trained on a larger dataset. As the figure demonstrates, augmenting with pseudo-pairs is beneficial for larger datasets as well.

spect there is a fundamental difference in the results. We suggest that this because in both of these experiments the dataset is completely pseudo-paired, i.e. there are no real samples of smiling images which leads the explicit method to overfit to the dataset and particularly to the features of the pseudo-smiles which are different from real smiles in some respects. This suggests that as long as the generation model $M(b)$ is not perfect, it would introduce features that the explicit method will overfit on, and the only efficient way to use the pseudo-samples might be in an implicit manner. In our Discussion section we explore the effect the artifacts introduced by $M(b)$ to the dataset has on the learned mappings.

Scalability experiments. Data augmentation is usually most effective when the size of the dataset is small and correspondingly our experiments were done with very small datasets (up to 4000 samples). We are interested in understanding whether learning with implicit pseudo-pairs is still beneficial with larger datasets. To accomplish this we repeat the basic experiments with datasets that are 5 times larger. Due to limits in the celebA dataset in these experiments we have 10K samples in each domain with additional 10K augmentation samples. Due to these restrictions we are also unable to repeat the natural augmentation experiment. The results shown in Table 7 and Figure 8 demonstrate that pseudo-pairs lead to impressive improvements even in large datasets.

5. Discussion and Conclusions

In Section 4.2 we demonstrate that augmenting the dataset with implicit pseudo-pairs boosts the performance of image-to-image translation models. In what follows, we further discuss and analyze the importance of the implicit pseudo-pairs in the unpaired image-to-image translation setting. We argue that these pseudo-pairs introduce an implicit mapping from which the model is able to learn a better inverse mapping.

To better understand the effect of the pseudo-pairs, we visualize the training and generated samples using several representations. We represent the space of identities using the OpenFace representation described in the previous section. The space of expressions is represented using a simple classifier trained on a subset of CelebA to distinguish be-
Figure 9. Pseudo-pairs visualized on representations not related to the task (space of identities) and representations related to the task (space of expressions) for the smile removal task. Above we use PCA to visualize smiling (in orange), neutral (in black) and augmented (in fuchsia), training samples.

**Pseudo-pairs as training samples.** In Figure 9, we visualize both representations on the training data. As Figure 9 illustrates, the distribution of the pseudo-samples is very similar to those of the smiling and neutral face distributions in respect to the space of identities, demonstrating that in terms of attributes not related to the translation task the pseudo-samples are indistinguishable from the real samples. The distribution of the expression representation, on the other hand, shows that the generation model $M(b)$ creates images that do not conform to the general CelebA distribution (as they are clearly mapped outside the space spanned by the smiling samples). While this is not surprising, as the pseudo-samples are, by definition, imperfect, it does raise the question of how these imperfect pseudo-samples positively affect the learned mapping.

**Samples generated using various augmentation settings.** To address the aforementioned question, we visualize the samples generated from the images belonging to the test set. We show the distribution created using the implicit pseudo-pairs method in Figure 10. To emphasize the correlation between the translated samples and the real samples in the target "neutral" domain, we fit ellipses to both sets. We compare these with ellipses fitted to the translation results of the baseline methods introduced in Section 4.2. As the figure illustrates, the learned translation for all baseline settings is somewhat similar, but the translation learned in the paired setting is significantly more distinct and creates samples which are classified more strongly as "neutral". To better quantify the differences, we measure the Euclidean distance between the center of the ellipse of the real samples and the center of the generated ones, as well as the average difference ratio between the major and minor axes. Our method obtains a Euclidean distance of 0.269 between the centers and an average difference ratio of 6% between the axes, while for the closest baseline the Euclidean distance to the real center is 1.172 and the average difference ratio with the real axes is 11%. This result illustrates that the model is able to detect the latent implicit signal within the dataset.

On the right of Figure 10, we compare the learned distributions of a completely pseudo-paired dataset learned either explicitly (with Pix2Pix) or implicitly (with CycleGAN). As discussed earlier, both implicit and explicit learning settings fail at completing the task (smile removal in this case) when trained over a completely pseudo-paired dataset. This is also evident in the figure, as the generated samples are not mapped to where real "neutral" images are mapped. As the figure illustrates, the implicit architecture seems to overfit to the identity signal which is implicitly provided in the pairs. On the other hand, the explicit architecture yields samples which are not spanned by the real images in the test set, and resembles the behavior of the pseudo-samples, as illustrated in Figure 9. This demonstrates that the explicit model is more strongly influenced by the noisy signal introduced by the pseudo-pairs.

**Conclusions.** It is well established that many of the most fundamental human abilities are learned implicitly. In this work, we analyzed the positive effect of learning with implicitly paired samples in an image-to-image translation problem. We have shown, through numerous experiments and examples, that learning from implicit pairs can effectively guide the network to learn a better mapping, more than additional unpaired or random samples.

We further analyzed the power of implicit learning using pseudo-pairs. These pseudo-pairs can be obtained automatically either using simple geometric models, as we have shown in the case of faces augmented with eyeglasses, or by more complicated models, such as neutral faces augmented with smiles. In both cases, implicitly providing the network with these pairs yields plausible mappings that better preserve non-task related information. Additionally, we have
shown that datasets augmented with pseudo-pairs can be significantly more effective in an unpaired setting than in a paired one.

The fact that the contribution of the implicit pairs is effective despite their signal being hidden across the dataset, raises the question of what other types of implicit signals may a deep neural network exploit effectively. In the future, we believe that exploring the mechanisms by which neural networks learn from implicit signals may shed light on the understanding of how neural networks learn in general and allow for finer control in the configuration of datasets.

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Architectures

CycleGAN

In all of our experiments with CycleGAN we have used the vanilla architecture that they have used with 9 residual blocks. Following the naming conventions used in [29] we express the generator layer parameters as follows: Define a $7 \times 7$ Convolution-InstanceNorm-ReLU layer with $k$ filters and stride 1 as $c7s1-k$, a $3 \times 3$ Convolution-InstanceNorm-ReLU layer with $k$ filters and stride 2 as $dk$, a residual block with $3 \times 3$ convolutional layers with equal numbers of filters on both layers as $Rk$, and a $3 \times 3$ fractional-strided-Convolution-InstanceNorm-ReLU layer with $k$ filters and stride $1/2$ as $uk$. For the discriminator we denote a $4 \times 4$ Convolution-InstanceNorm-LeakyReLU layer with $k$ filters as $Ck$.

Using these definitions the generator network can be expressed as:
\[ c7s1-64, d128, d256, R256, R256, R256, R256, R256, R256, R256, u128, u64, c7s1-3 \]

The discriminator network can be similarly expressed as:
\[ C64 - C128 - C256 - C512 \]

The implicit pairs experiments 4.1 were done with a batch size of 1. The implicit pseudo-pairs experiments 4.2 were done with a batch size of 10.

Pix2Pix

All experiments involving the Pix2Pix architecture were done using the vanilla version as well. Using the conventions used in [11] for the Pix2Pix network we denote the Convolution-BatchNorm-ReLU layer with $k$ filters as $Ck$ and the Convolution-BatchNorm-Dropout-ReLU layer with 50% dropout rate as $CDk$.

The generator is comprised of an encoder expressed as:
\[ C64 - C128 - C256 - C512 - C512 - C512 - C512 - C512 \]
and a decoder expressed as:
\[ CD512 - CD512 - CD512 - C512 - C256 - C128 - C64 \]

The discriminator can be expressed as:
\[ C64 - C128 - C256 - C512 \]

The implicit pairs experiments 4.1 were done with a batch size of 1. The implicit pseudo-pairs experiments 4.2 were done with a batch size of 10.

FCN-score

labels $\rightarrow$ photo  In this direction we use the same FCN-8 network that was used in [11] to segment the generated image into a label matrix.

Finally in either direction we used the evaluation script provided in Zhu’s github repository ¹

CVC-14 dataset

The dataset contains paired sequences of road scenes taken during the day and during the night. To break the temporal dependence between the frames we only sample every 100-th frame from the day sequences.

¹https://github.com/junyanz/pytorch-CycleGAN-and-pix2pix

labels $\rightarrow$ photo

To convert the generated image to a label matrix we mapped every pixel’s rgb value to the label with the lowest mean distance according to the label↔rgb value conversion table provided with the Cityscapes [7] dataset.
Figure 11. Additional examples of the effect of learning image-to-image translation with varying pairing ratios
Figure 12. Additional results for the smile removal task using different dataset configurations. Above we illustrate our randomly selected results (on the right) compared against three augmentation baselines, described in Section 4.2.

Figure 13. Additional Eyeglass removal results using different dataset configurations. Above we illustrate our randomly selected results (on the right) compared against three augmentation baselines, described in Section 4.2.
Figure 14. Additional pseudo-pair ratio analysis results for the smile removal task

Figure 15. Additional pseudo-pair ratio analysis results for the eye-glass removal task
Figure 16. Additional *Smile removal* results with pseudo-pairs in different settings.