Reducing the Amount of Real World Data for Object Detector Training with Synthetic Data

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Abstract—A number of studies have investigated the training of neural networks with synthetic data for applications in the real world. The aim of this study is to quantify how much real world data can be saved when using a mixed dataset of synthetic and real world data. By modeling the relationship between the number of training examples and detection performance by a simple power law, we find that the need for real world data can be reduced by up to 70% without sacrificing detection performance. The training of object detection networks is especially enhanced by enriching the mixed dataset with classes underrepresented in the real world dataset. The results indicate that mixed datasets with real world data ratios between 5% and 20% reduce the need for real world data the most without reducing the detection performance.

I. INTRODUCTION

Reliable and robust object detection is one of the key techniques for autonomous driving. However, the training of neural networks for object detection requires a huge amount of labeled data for which collecting and labeling in the real world is a time-consuming and expensive task. Especially the collection of edge or corner cases for the dataset is challenging, because it is virtually impossible to capture all edge cases imaginable or even a significant amount of it. A systematic overview of edge cases can be found in [1]. Another problem of real world automotive datasets is that there is usually a strong imbalance in the occurrence of classes: car is the dominant class while vulnerable road users like pedestrians and bicycles occur less frequently. An additional challenge is the need for anonymization of real world data to comply with the General Data Protection Regulation (GDPR). To be compliant with the General Data Protection Regulation (GDPR) real world data has to be usually anonymized, which adds a post-processing step to the data pipeline.

Synthetic data can be easily constructed in ways, that it has none of the drawbacks mentioned above: Ground truth data can be generated with pixel level accuracy. It is even possible to generate these data "on the fly" without the need to store the data and thus storage costs can be traded for compute costs [2]. Even rare and dangerous scenarios can be simulated. The class imbalance in synthetic datasets can also be circumvented by adding additional instances of underrepresented classes to the synthetic dataset. In addition, synthetic data does not suffer from any legal issues related to the GDPR. However, the domain gap prevents object detectors trained only on synthetic data from reaching the same performance as their counterparts trained on an equal number of real training examples [3], [4].

To overcome this problem mainly two different training strategies are usually applied: One kind of approaches uses pretraining and fine-tuning strategies to pretrain a network on synthetic data and later fine-tune on real data. Another group of approaches is mixed strategies, where the networks are trained simultaneously on real and synthetic data in a mixed training dataset. Usually for both types of strategies the training does not start from scratch but from network backbones trained on real data as e.g. ImageNet [5] or COCO [6].

More specifically, several concrete approaches to combine synthetic and real data for training have been applied so far. For example Trembaly et al. proposed pretraining on synthetic training examples, which are generated by a domain randomization approach [7]. Objects with random textures are placed in random backgrounds with additional random objects as distractors. Fine-tuning these pretrained networks on real data improved the performance of the object detection network compared to only training on real data. However, their study focused on the dominant car class in automotive datasets and did not deal with vulnerable road users.

As an example for the second group of strategies, Nowruzi et al. studied the effect of different ratios of real and synthetic data in the training dataset as well as pretraining and fine-tuning vs. a mixed strategy [8]. They used various synthetic datasets (Synscapes [9], GTA [10], Carla [11]) and real datasets (BDD [12], Cityscapes [13], KITTI [14], Nuscenes [15]) and concluded that pretraining on synthetic data and fine-tuning on real data provides better results than mixed training. Although their results showed, that higher ratios of real data in the training dataset are beneficial, only ratios of real data up to 10% were investigated.

However, when choosing generally mixed training sets as basic strategy, it is still unclear, what the best ratio of real and synthetic data would be. Also, the actual criteria, to get the "best" ratio can still be defined in several ways. This study focuses on determining how much real data can be saved when using synthetic data. Therefore, an evaluation method based on a simple power law is proposed to quantify real data saving in mixed real and synthetic datasets. In addition, the influence of adding synthetic instances of underrepresented vulnerable road users (person class) is studied.

Apart from 3D rendering approaches to produce synthetic data, generative adversarial networks (GANs) are a
promising alternative to generate synthetic data [16], [17]. To investigate the possibility of using GAN images for training neural networks, an additional synthetic dataset is created from the Synscapes semantic segmentation by an image-to-image translation GAN [18]. This dataset is referred to as “GANscapes”.

II. METHOD

To evaluate the proposed experiments real and synthetic datasets with the same labeling specifications for ground truth labels are needed. Cityscapes [13] was selected as the real world dataset and the Synscapes dataset [9] with \( N_{\text{syn}} = 25000 \) examples was chosen as the synthetic dataset.

In addition to the labeling specifications, many parameters in Synscapes like camera pose and field of view are identical to the corresponding Cityscapes parameters. Some typical examples of Cityscapes and Synscapes images are shown in Fig. 1. The Synscapes dataset puts its emphasis on classes usually underrepresented in autonomous driving datasets like persons. Fig. 2 shows class imbalances of the two used datasets. While in Cityscapes the car class is the dominant class, in Synscapes the most frequent class is deliberately shifted towards the person class.

Since the Synscapes dataset does not distinguish between riders and rideable objects (bicycles and motorcycles) a preprocessing step was performed on the Cityscapes dataset where riders were merged with the closest rideable object to the class bicycle or motorcycle.

The Cityscapes dataset contains 2975 labeled training images, 500 labeled validation images, and 1525 test images, for which the ground truth labels are withheld for the official benchmark. Therefore, the Hamburg sequence with 248 images was used as the new validation set, which leaves \( N_{\text{city}} = 2727 \) examples in our real world training dataset. The 500 original validation images were used as the new test set on which all trained object detection networks were evaluated.

The GANscapes dataset was generated from the semantic and instance segmentation images of the Synscapes dataset with a pix2pixHD network [18]. For the experiments the original implementation with weights from training on Cityscapes was used. Since Synscapes does not differentiate between the rider class and the bicycle or motorcycle class, the quality of GAN generated bicycles and motorcycles might be negatively affected. However, by looking at some generated bicycles and motorcycles (see e.g. last row in Fig. 1), the quality is comparable to the input from Cityscapes semantic and instance segmentation. To further improve the quality of the generated images, the faces of semantic segmentation covering the always visible front view of the recording car are added to Synscapes semantic segmentation.

To analyze the detection performance of the trained networks with the proposed power law, the networks have to be trained on a varying (ideally logarithmically spaced) number of total training examples \( N_{r,i} \), where \( r \) denotes the ratio of real world examples and an index \( i = 1, \ldots, 10 \). These training subsets are constructed by randomly drawing (without replacement) \( r N_{r,i} \) examples from the \( N_{\text{city}} \) Cityscapes examples and \( (1-r)N_{r,i} \) examples from the \( N_{\text{syn}} \) synthetic examples. For example, a training subset with \( N_{20\%,1} = 272 \) examples consists of 54 examples randomly selected from the \( N_{\text{city}} \) examples. The remaining 218 examples are either selected from the \( N_{\text{syn}} \) Synscapes examples, when training on a mixed Cityscapes+Synscapes dataset or selected from \( N_{\text{syn}} \) GANscapes examples when training on a mixed Cityscapes+GANscapes dataset.

For the object detection network a YOLOv3 architecture [19] was chosen, which was pretrained on the COCO dataset. The YOLOv3 is trained with a batch size of 16, an initial learning rate of \( 3 \cdot 10^{-4} \) and a cosine learning rate schedule without restarts [20] is employed. The training data is augmented via random color jitter, random crop, and random mosaicking [21]. The network is trained until no improvement on the validation set is observed for 20 epochs.

For every number of training examples \( N_{r,i} \) the training was repeated five times with different initializations of the YOLOv3 detection head and different random selections of training examples.

III. RESULTS AND DISCUSSION

A. Pretraining + fine-tuning vs. mixed training strategy

Results in a previous study [8] indicated that pretraining a neural network on synthetic data and fine-tuning on real data is a better training strategy than training on a mixed dataset of synthetic and real data. However, no confidence intervals are reported for their findings. Therefore, a YOLOv3 network pretrained on COCO was on the one hand pretrained on 25000 synthetic examples and subsequently fine-tuned on 2727 real examples and on the other hand trained on a mixed dataset consisting of all synthetic and real examples. Both training strategies were repeated five times with different random seeds. The performance of the trained networks on the test set with 500 real examples is evaluated in terms of mean average precision (mAP) and average precision (AP) [22], [23]. The metrics require an intersection over union (IoU) threshold at which a predicted bounding box is considered a match with a ground truth bounding box. A threshold of \( \text{IoU} \geq 50\% \) is chosen throughout all experiments (mAP\(_{50}\), AP\(_{50}\)). Tab. I shows the resulting mAP\(_{50}\) and AP\(_{50}\) values for the car and person class averaged over five training runs with the standard deviation. No significant difference between the pretraining + fine-tuning and the mixed training strategy was observable.

B. Reduction of real data amount by adding synthetic data

As outlined in the introduction, neural networks trained only on synthetic data generalize poorly to real world data. Considering Fig. 3 the previous statement can be confirmed: When the mAP\(_{50}\) scores of networks trained on different ratios of real and synthetic data are compared, networks trained on real data only (red triangles, real data portion of
Fig. 1. Example images from the Cityscapes dataset (top row), the Synscapes dataset (middle row) and our generated GANscapes dataset from the Synscapes semantic segmentation (last row).

Fig. 2. Average instances per image for different classes in the Cityscapes and Synscapes/GANscapes dataset.

100%) outperform significantly their counterparts trained on synthetic data only (purple squares, real data portion of 0%). These results are consistent for the Synscapes dataset Fig. 3a and the GANscapes dataset Fig. 3b.

In Fig. 3 we compare the model performance for different ratios $r$ of real data dependent on the total number of training examples. In agreement with results by Hestness et al., the performance improvement by increasing the number of training examples can be described by a power law \cite{24} of the form

$$1 - m\text{AP}_{50} = 10^\beta N_{r,i}^{\gamma},$$

(1)

where $\beta$ and $\gamma$ are the intercept and the slope of the linear fit in the log-log plot. It can be seen in Fig. 3 that the slope parameter $\gamma$ decreases when ratio $r$ of real data is increased, indicating better training results when more real data is included in the training dataset. The $m\text{AP}_{50}$ scores of networks trained on mixed datasets surpass the best $m\text{AP}_{50}$ score for networks trained only on the real data ($r = 100\%$) with the maximum number of training images ($N_{100\%,10} = 2727$). However, by taking into account the standard deviations, the performance increase is not significant in most cases.

The amount of training examples needed to reach the best performance of the networks trained only on real data (intersection of colored dashed lines with horizontal black dashed line in Fig. 3a and Fig. 3b) can be easily obtained from Eq. (1). The calculated numbers of total training examples are shown in Table I.

| Class Label | $m\text{AP}_{50}$ | $\text{AP}_{50}$ |
|-------------|-----------------|----------------|
| bicycle     | pretrain + fine-tune | mixed         |
| car         | pretrain + fine-tune | mixed         |
| trailer     | pretrain + fine-tune | mixed         |
| train       | pretrain + fine-tune | mixed         |
| truck       | pretrain + fine-tune | mixed         |

$m\text{AP}_{50}$ and $\text{AP}_{50}$ for the car and person class for both considered training strategies with a ratio of 10% real data.
Fig. 3. Performance of neural networks in terms of 1-mAP$_{50}$ (lower is better) for various ratios of real data in the mixed dataset consisting of real data and Synscapes (left side) and GANscapes (right side). Values are presented as mean values and standard deviations over five training runs. Dashed colored lines are regression lines fitted with Eq. (1). The dashed horizontal black is an auxiliary line to help the reader compare detection performance with the mean performance of the networks trained on all 2727 real examples.

### TABLE II

| Ratio of real data | Synscapes Total images | Synscapes Real images | GANscapes Total images | GANscapes Real images |
|-------------------|------------------------|-----------------------|------------------------|-----------------------|
| 5%                | 18166                  | 908                   | 16804                  | 840                   |
| 10%               | 7783                   | 778                   | 9335                   | 933                   |
| 20%               | 5685                   | 1137                  | 5217                   | 1043                  |
| 50%               | 2427                   | 1214                  | 2783                   | 1392                  |
| 100%              | 2727                   | 2727                  | 2727                   | 2727                  |

While there is a substantial increase in the total number of required training examples, the amount of real data examples decreases dramatically. In the best case (10% real images with Synscapes) only around 30% of the original real data were needed. The results from Tab. III suggest that the best ratio of real data in a mixed training dataset is between 5% and 20%. The GANscapes dataset achieves comparable results in terms of real data reduction.

### C. Class influence on data reduction

The results shown for the mAP$_{50}$ score were obtained by averaging over all classes in the dataset, which masks the influence of specific classes. It is therefore interesting to analyze the detection performance for different classes in terms of AP$_{50}$ score. As an example the car class (most frequent class in real dataset) and the person class (most frequent class in synthetic dataset) were investigated in more detail. From Fig. 4a and Fig. 4b, it can be seen that adding synthetic examples to the training dataset does not deteriorate the detection performance of networks evaluated on the car class significantly. Fig. 4c and Fig. 4d show the same for the person class. The networks trained on mixed datasets exceed the detection performance of the networks trained on real data for the person class. However, the performance increase is not significant except for the training with $r = 10\%$ with Synscapes data.

The real data saving results are presented in Tab. III for the car class and in Tab. IV for the person class. A large discrepancy between the car and the person class occurs when the mixed datasets are compared in terms of real world data reduction. For the car class the lowest amount of real data examples required is still as much as 64% while for the person class only 20% of the real world dataset is needed (5% real with Synscapes). This can be expected, because the real world dataset already contains a lot of car instances and hence the benefit by adding synthetic instances is small. Since the person class is underrepresented in the real dataset, the network benefits to a greater extent from the additional synthetic instances. Another interesting result is that the person assets, which were generated in Synscapes with a lot of effort, can be exchanged with GAN images without compromising too much reduction of real world data examples in the training dataset.

### IV. CONCLUSIONS

This study extends the research on the use of synthetic data for neural network training. In contrast to [8], no significant difference of the detection performance was found, when pretraining on synthetic data first and fine-tuning on real data.
or when training on a mixed dataset of real and synthetic examples.

We showed that synthetic data can be used to reduce the need for real world data in a mixed training dataset. The proposed method enabled us to estimate that the most reduction of real examples can be achieved with a ratio of real examples between 5% and 20% in mixed training datasets. In addition, we showed that neural networks can particularly benefit from synthetic data, when the synthetic data is enriched with classes that are underrepresented in the real world dataset. Since synthetic data can usually be produced in a much more cost-efficient way, mostly because ground truth labeling comes for free in synthetic data, this is a promising approach for autonomous driving, where real world labeled data is still rather expensive.

While synthetic datasets generated by GANs are not as good as synthetic datasets produced by classical methods, they are a promising alternative as the technology is still evolving. Especially the need for modeling high fidelity 3D assets can be circumvented by GANs. However, current GANs often need semantic (instance) segmentation images for their training, which is even more expensive than bounding box labeling.

Although the results are promising, our study only evaluated one real dataset and two synthetic datasets for a single object detection architecture. Future work should therefore extend our proposed method for the evaluation of reduction of real data in mixed training datasets to additional real
and synthetic datasets as well as additional object detection architectures.

REFERENCES

[1] J. Breitenstein, J.A. Termöhlen, D. Lipinski, and T. Fingscheidt, "Systematization of Corner Cases for Visual Perception in Automated Driving", IEEE Intelligent Vehicles Symposium (IV), Las Vegas, 2020, pp. 986.

[2] K. Mason, S. Vejdan, and S. Grijalva, "An "On The Fly" Framework for Efficiently Generating Synthetic Big Data Sets" 2019 IEEE International Conference on Big Data, Los Angeles, 2019, pp. 3379.

[3] W. Chen, Z. Yu, Z. Wang, and A. Anandkumar, "Automated synthetic-to-real generalization", International Conference on Machine Learning, PMLR 2020 pp. 1746 - 1756.

[4] W. Chen, Z. Yu, S. De Mello, S. Liu, J.M. Alvarez, Z. Wang, A. Anandkumar, "Contrastive Syn-to-Real Generalization", International Conference on Learning Representations, online, 2021.

[5] J. Deng, W. Dong, R. Socher, L.J. Li, K. Li, and L. Fei-Fei, "ImageNet: A large-scale hierarchical image database", IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Miami, 2009.

[6] Y. Lin, M. Maire, S. Belongie, J. Hays, P. Perona, D. Ramanan, D. Darrell, "Microsoft COCO: Common Objects in Context", European Conference on Computer Vision (ECCV), Zurich, 2014, pp. 740.

[7] J. Tremblay, A. Prakash, D. Acuna, M. Brophy, V. Jampani, C. Anil, T. To, E. Cameracci, S. Boochoon, and S. Birchfield, "Training deep networks with synthetic data: Bridging the reality gap by domain randomization," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops.

[8] F.E. Nowrui, P. Kapoor, D. Kolhatkar, F.A. Hassanat, R. Laganiere, and J. Rebut, "How much real data do we actually need: Analyzing object detection performance using synthetic and real data", ICML Workshop on AI for Autonomous Driving, Long Beach, 2019.

[9] M. Wrenninge and J. Unger, "Synscapes: A Photorealistic Synthetic Dataset for Street Scene Parsing", CoRR, abs/1810.08705, 2018.