

# Deep Learning Reproducibility and Explainable AI (XAI)

A.-M. Leventi-Peetz  
 Federal Office for Information Security (BSI) Germany  
 leventi@bsi.bund.de

T. Östreich  
 Federal Office for Information Security (BSI) Germany

## Abstract

The nondeterminism of Deep Learning (DL) training algorithms and its influence on the explainability of neural network (NN) models are investigated in this work with the help of image classification examples. To discuss the issue, two convolutional neural networks (CNN) have been trained and their results compared. The comparison serves the exploration of the feasibility of creating deterministic, robust DL models and deterministic explainable artificial intelligence (XAI) in practice. Successes and limitation of all here carried out efforts are described in detail. The source code of the attained deterministic models has been listed in this work. Reproducibility is indexed as a development-phase-component of the Model Governance Framework, proposed by the EU within their excellence in AI approach. Furthermore, reproducibility is a requirement for establishing causality for the interpretation of model results and building of trust towards the overwhelming expansion of AI systems applications. Problems that have to be solved on the way to reproducibility and ways to deal with some of them, are examined in this work.

## 1 Introduction

### 1.1 Reproducible ML models

The reproducibility of ML models is a subject of debate with many aspects under investigation by researchers and practitioners in the field of AI algorithms and their applications. Reproducibility refers to the ability to duplicate prior results using the same means as used in the original work, for example the same program code and raw data. However, ML experiences what is called a reproducibility crisis and it is difficult to reproduce important ML results, some also described as *key results* [26, 25, 13, 32]. Experience re-

ports refer to many publications as being not replicable, or being statistically insignificant, or suffering from narrative fallacy [5]. Especially Deep Reinforcement Learning has received a lot of attention with many papers [5, 31, 29, 14] and blog posts [28] investigating the high variance of some results. Because it is difficult to decide which ML results are trustworthy and generalize to real-world problems, the importance of reproducibility is growing. A common problem concerning reproducibility is when the code is not open-sourced. The review of 400 publications of two top AI conferences in the last years, showed that only 6% of them shared the used code, one third shared the data on which algorithms were tested and half shared pseudocode [20, 27]. Initiatives like the *2019 ICLR reproducibility challenge* [34] and the *Reproducibility Challenge of NeurIPS 2019* [38, 17], that invite members of the AI community to reproduce papers accepted at the conference and report on their findings via the Open-Review platform ([https://openreview.net/group?id=NeurIPS.cc/2019/Reproducibility\\_Challenge](https://openreview.net/group?id=NeurIPS.cc/2019/Reproducibility_Challenge)), demonstrate an increasing intention to make machine learning trustworthy by making it computationally reproducible [23]. Reproducibility is important for many reasons: For instance, to quantify progress in ML, it has to be certain that noted model improvements originate from true innovation and are not the sheer product of uncontrolled randomness [5]. Also from the development point of view, adaptations of models to changing requirements and platforms are hardly possible in the absence of baseline or reference code, which works according to agreed upon expectations. The latter could get transparently extended or changed before tested to meet new demands. For ML models, it is the so named *inferential reproducibility* which is important as a requirement and states that when the inference procedure is repeated, the results should be qualitatively similar to those of the original procedure [13]. However, training reproducibility is also a necessary step towards

the formation of a systematic framework for an end-to-end comparison of the quality of ML models. To our knowledge such a framework does not yet exist and it should be essential if criteria and guarantees regarding the quality of ML models have to be provided. Security and safety considerations are inevitably involved: For instance, when a model executes a pure classification exercise, deciding for example if a test image shows a cat or a dog, it is not necessarily critical when the model's decision turns out to be wrong. If however the model is incorporated into a clinical decision-making system, that helps make predictions about pathologic conditions on the basis of patients' data, or is part of an automated driving system (ADS) which actively decides if a vehicle has to immediately stop or keep speeding, then the decision has to be verifiably correct and understandable at every stage of its formation. The increasing dependency on ML for decision making leads to an increasing concern that the integration of models which have not been fully understood can lead to unintended consequences [24].

## 1.2 Factors hindering training reproducibility

It is well known that when a model is trained again with the same data it can produce different predictions [8, 7]. To the reasons that make reproducibility difficult there belong: different problem formulations, missing compatibility between DNN-architectures, missing appropriate benchmarks, different OS, different numerical libraries, system architectures or software environments like the Python version etc. Reproducibility as a basis for the generation of sound explanations and interpretations of model decisions is also essential in view of the immense computational effort and costs involved when applying or adapting algorithms, often without specific knowledge about the hardware, the parameter-tuning and the energy consumption demanded for the training of a model, which at the end might lead to inconclusive results. Furthermore, it is also difficult to train models to expected accuracy even when the program code and the training data are available. Changes in TensorFlow, in GPU drivers, or even slight changes in the datasets, can hurt accuracy in subtle ways [46, 45]. In addition, many ML models are trained on restricted datasets, for example those containing sensitive patient information, that can't be made publicly available [1]. When privacy barriers are important considerations for data sharing, so called replication processes have to be used, to investigate the extent to which the original model generalizes to new contexts and new data populations, and decide whether similar conclusions to

those of the original model can be delivered. However, there exist also certain unique challenges which ML reproducibility poses. The training of ML models makes use of randomness, especially for DL, usually employing stochastic gradient descent, regularization techniques etc. [3]. Randomized procedures result in different final values for the model parameters every time the code is executed. One can set all possible random seeds, however additional parameters, commonly named silent parameters, associated with modern deep learning, have been found to also have a profound influence on both model performance and reproducibility. High-level frameworks like Keras are reported to hide low-level implementation details and come with implicit hyperparameter choices already made for the user. Also hidden bugs in the source code can lead to different outcomes in dependence of linked libraries and different execution environments. Moreover, the cost to reproduce state-of-the-art deep learning models is often extremely high. In natural language processing (NLP), *transformers* require huge amounts of data and computational power and can have in excess of 100 billion trainable parameters. Large organizations produce models (like OpenAI's GPT-3) which can cost millions of dollars in computing power to train [1, 3, 12]. To find the transformer that achieves the best predictive performance for a given application, *meta-learners* test thousands of possible configurations. The cost to reproduce one of the many possible transformer models has been estimated to range from 1 million to 3.2 million USD with usage of publicly available cloud computing resources [39, 3]. This process is estimated to generate CO<sub>2</sub> emissions with a volume which amounts to the fivefold of emissions of an average car, generated over its entire lifetime on the road. The environmental implications attached to reproducibility endeavors of this range are definitely prohibitive [3]. As possible solution to this problem, there has been proposed the option to let expensive large models get produced only once, while adaptations of these models for special applications should be made transparent and reproducible with the use of more modest resources [3].

## 1.3 Organization and aim of this work

The majority of methods for explainable AI are attribute based, they highlight those data features (attributes), that mostly contributed to the model's prediction or decision. Convolutional neural networks (CNN, or ConvNet) are state-of-the-art architectures, for which visual explanations can be produced, for example with the Gradient-weighted Class Activation Mapping method (Grad-CAM) [37, 11], which is also

the method used in this work. In the second part of this work, Grad-CAM explanations for two pre-trained and established CNN models, which use TensorFlow, will be discussed with focus on the differences of their results, when the same test-data are given as input. It is well known that when different explainability methods are applied on a neural network, different results are to be expected. The fact that a single explainability method, when applied on two similar CNN-architectures, can produce different results for the same test-data, has received less attention in the literature but is worth to analyze in the reproducibility context. In the third part, the own implementation, training and results of two relatively simple CNN models are discussed. Differences of the Grad-CAM-explanations for identical images classified with these two networks are analyzed, with special focus on the influence of the computing infrastructure on the model execution. The efforts to render these two models deterministic are described in Section 3 in detail, again with special focus on the influence of the computing infrastructure on the results. Success and limitations are noted, the partly achieved deterministic code is listed. It is worth mentioning that different behaviors across versions of TensorFlow, as well as across different computational frameworks are documented to be normally expected. TensorFlow warns that floating point values computed by ops, may change at any time and users should rely only on *approximate accuracy and numerical stability, not on the specific bits computed*. There could be found no experience reports, as to how a change of *specific bits* could influence ML results, for instance in worst case by altering the network’s classification or its explanation, or both. According to TensorFlow, changes to numerical formulas in minor and patch releases, should result in comparable or improved accuracy of specific formulas, with the *caution* that this might *decrease the accuracy* for the overall system. Also models implemented in one version of TensorFlow, cannot run with next subversions and versions of TensorFlow. Therefore published code which was once proved to work, is possibly not to use again within short time after its creation. To run more than one subversions on the same system, when using graphic HW support, was not possible. This work aims at drawing attention to the challenges that adhere to creating reproducible training processes in Deep Learning and demonstrates practical steps towards reproducibility, discussing their present limitations. In Section 4 conclusions of this work and views towards future investigations in the same direction are presented in a summary. It has to be noted that the impact of what is called *underspecification*, whereby the same training processes produces multi-

ple machine-learning models which demonstrate differences in their performance, is out of scope of this work [22].

## 2 Grad-CAM NN-Explanations

### 2.1 Network architectures and HW

Convolutional neural networks, originally developed for the analysis and classification of objects in digital images, represent the core of most state-of-the-art computer vision solutions for a wide variety of tasks [42]. A brief but comprehensive history of CNN can be found in many sources, for example in [9], whereby the tendency has always been towards making CNN increasingly deeper. Developments of the last years have led to the *Inception architecture*, which incorporates the so called *Inception modules*, that exist already in several different versions. A new architecture, which instead of stacks of simple convolutional networks, contains stacks of convolutions itself, was proposed by François Chollet with his *Extreme Inception* or *Xception* model. Xception was proved to be capable of learning richer representations with less parameters [9]. Chollet delivered the Xception improvements to the Inception family of NN-architectures, by entirely replacing Inception modules with depthwise separable convolutions. Xception also uses residual connections, placed in all flows of the network [9, 21]. The role of residuals was observed as especially important for the convergence of the network [44], however Chollet moderates this importance, because non-residual models have been benchmarked with the same optimization configuration as the residual ones, which leaves the possibility open, that another configuration might have proved the non-residual version better [9]. Finally, the building of the improved Xception models was made possible because an efficient depthwise convolution implementation became available in TensorFlow. The Xception architecture has a similar number of parameters as Inception V3. Its performance however has been found to be better than that of Inception, according to tests on two large-scale image classification tasks [9]. For practical tests in this work, Inception V3 and Xception have been chosen for results comparisons. The two networks are pretrained on a trimmed list of the ImageNet dataset, so as to be able to recognize one thousand non-overlapping object classes [9].

**Inception V3** The exact description of the network, its parameters and performance are given in the work of Christian Szegedy [41]. The description of the training infrastructure refers to a

system of 50 replicas, (probably identical systems), running each on a NVidia Kepler GPU, with batch size 32, for 100 epochs. The time duration of each epoch is not given.

**Xception** Chollet has used 60 NVIDIA K80 GPUs for the training, which took a duration of 3 days time. The number of epochs is not given. The network and technical details about the training are listed in the original work [9].

Xception has a similar number of parameters (ca. 23 million) as Inception V3 (ca. 24 million). The HW execution environments employed for the here described experiments are the following:

- HW-1: GPU: NVIDIA TITAN RTX: 24 GB (GDDR6), 576 NVIDIA Turing mixed-precision Tensor Cores, 4608 CUDA Cores.
- HW-2: CPU: AMD EPYC 7502P 32-Core, SMT, 2 GHz (T: 2.55 GHz), RAM 128 GB.
- HW-3: GPU: NVIDIA GeForce RTX 2060: 6 GB (GDDR6), 240 NVIDIA Turing mixed-precision Tensor Cores, 1920 CUDA Cores.
- HW-4: CPU: AMD Ryzen Threadripper 3970X 32-Core, SMT, 3.7 GHz (T: 4.5 GHz), RAM 256 GB.
- HW-5: CPU: AMD Ryzen 7 5800X 8-Core, SMT, 3.8 GHz (T: 4.7 GHz), RAM 64 GB.

Each of the pretrained models is verified to deliver the same results for all here considered CPU or GPU different execution environments. The classifications and the according network explanations are deterministic when performed under laboratory conditions, as also expected. Plausibility and stability issues of the explanations will be mentioned parallel to the tests.

## 2.2 Inception V3

In this part examples of predictions, calculated with the Inception V3 network are discussed. In Fig. 1 (a) and (b) respectively, there are depicted activation heatmaps which have been produced to identify those regions of the image *chow-cat*, that correspond to the dog (“chow”) and the cat (“tabby”) respectively. Identical respective accuracies have been calculated for each classification independent of the employed HW, as was verified by the tests performed with all HW-environments listed at the end of 2.1. The “chow” has been predicted with 30% probability and stands in the first place on the top-predictions-list, while the cat gets the third position with a probability of 2.4%. In Fig. 2, heatmaps produced by the identification of the “cocker spaniel” (a), the “toy poodle” (b), and the “Persian cat” (c) respectively, have been demonstrated



Figure 1. *chow-cat*: Grad-CAM explanations of Inception V3 for the identification of the dog “chow” (a), in the first place on the top-predictions-list and the cat “tabby”(b), in the third place on the top-predictions-list. The second place occupies a “Labrador dog”.

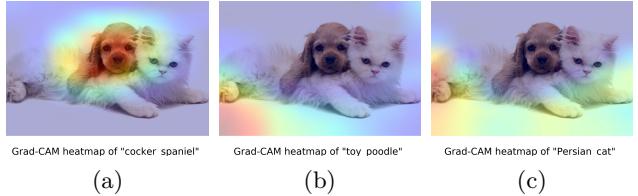


Figure 2. *spaniel-kitty*: Grad-CAM explanation of Inception V3 for the identification of the “cocker spaniel” (a), the “toy poodle” (b) and the “Persian cat” (c), see Table 1.

Table 1. Inception V3: Classification Probabilities for the image *spaniel-kitty*, see Fig. 2.

	Class	HW-2	HW-1
1	cocker spaniel	0.56762594	0.56761914
2	toy poodle	0.08013367	0.08014054
3	clumber	0.02106595	0.02107035
4	Dandie Dinmont	0.01964365	0.01964012
5	Pekinese	0.01867950	0.01868443
6	miniature poodle	0.01846011	0.01846663
7	Blenheim spaniel	0.01425239	0.01424699
8	Maltese dog	0.01124849	0.01124578
9	Chihuahua	0.01103328	0.01103479
10	Norwich terrier	0.00741338	0.00741514
11	Sussex spaniel	0.00703137	0.00703068
12	Yorkshire terrier	0.00689254	0.00689154
13	Norfolk terrier	0.00662250	0.00662296
14	Lhasa	0.00609926	0.00609862
15	Pomeranian	0.00608485	0.00608792
16	Persian cat	0.00489533	0.00489470
17	golden retriever	0.00428663	0.00428840

Table 2. Inception V3: Classification Probabilities for the image *spaniel-kitty-paws-cut*.

	Class	HW-2	HW-1
1	cocker spaniel	0.43387938	0.43393657
2	Persian cat	0.03001592	0.03000891
3	Pekinese	0.02654952	0.02654130
4	toy poodle	0.01810920	0.01810851
5	Dandie Dinmont	0.01457902	0.01457707
6	Sussex spaniel	0.01415453	0.01415372
7	Golden retriever	0.01363987	0.01363916
8	Miniature poodle	0.01088122	0.01088199

for the image *spaniel-kitty*. In Table 1 there are listed the scores of the first 17 classes on the top-predictions-list, as calculated in two HW executions (HW-1,HW-2). The prediction scores are almost identical, as is obvious by comparing the columns in Table 1, while in the few cases, when slight differences exist in the probability values, these differences appear only after the fourth decimal place. The “cocker spaniel” is the top prediction and represents actually the correct classification of the dog race, predicted with a probability of almost 57%, while the “Persian cat” in place 16 of the list, which is also a correct prediction, has a probability of approximately 0.5%. The “toy poodle” with 8.0% probability stands in the second place on the list, while the rest of list places, down to place sixteen of the “Persian cat”, are all occupied by dog races (see Table 1).

### 2.2.1 Soundness and stability of explanations

A careful observation of the delivered network explanations shows that they are partly arbitrary and hardly intuitive, and this independently of a wrong, or right class prediction. For example, the network reasoning behind the “toy poodle” classification in Fig. 2 (b), which is wrong as far as the race of the dog is concerned, but right as far as the animal category identified (a dog), cannot be noted as sound. The main reason is because the most activated, and therefore the most relevant to the target identification region (marked red), points to a part of the image that lies in empty space, beyond the contour of the target. The marked red region lies close to what one could describe as a *generic feature*, the paws, which is common to a variety of animals. A too *generic feature* offers little confidence in being a good explanation, if assumed that it is only the accuracy of the feature’s localization in the image that fails. Besides, the algorithm could have focused on the vicinity of the paws out of reasons not directly associated with the recognition of the

“poodle”. Observing that the explanation for the identification of the “Persian cat”, see Fig. 2 (c), highlights the same paws, makes the unambiguity or definiteness of the explanations questionable. Important is also the investigation of the *stability* and *consistency* of the network’s explanations, as they relate to the reproducibility of the network too. For example, it would be expected that a network which concentrated on the dog’s head to explain the first place of the top-predictions-list, the “cocker spaniel” in Fig. 2 (a), would probably also pick the head to mainly identify the second most probable classification on the list, which the “toy poodle”, seen in Fig. 2 (b). This is however not the case, which makes the consistency behind the logic of explanations doubtful. Obviously, the cat’s head also receives hardly any attention for the explanation of the recognition of the cat in 2 (c). It is not possible to identify some certain strategy which the network consistently employs in order to explain classifications, in this case of animals. For further investigations, a small part of the image *spaniel-kitty*, namely the part containing the paws, has been removed from the image and the top-predictions-list has been calculated again. With the new test image, *spaniel-kitty-paws-cut* as input, the “cocker spaniel” keeps the first place on the top-predictions-list, see Table 2, however the “Persian cat” climbs now from place 16 to place 2 with a classification probability rising from 0.5% to 30%, while the “toy poodle” falls down to the place 4 of the list. In Table 2, the new top-four predicted classes and their new scores are displayed. There are no great changes in the explanation concerning the “cocker spaniel” for the modified image, the head being the part highlighted again. However the visual explanations for the identification of the “toy poodle” and the “cat” have changed considerably, as in Fig. 3 to see. The “toy poodle”

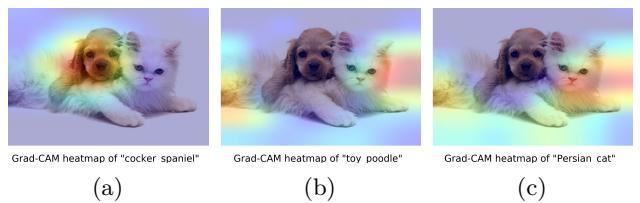


Figure 3. *spaniel-kitty-paws-cut*: Grad-CAM explanation of Inception V3 for the identification of the “cocker spaniel” (a), the “toy poodle” (b) and the “Persian cat” (c), when the paws are removed from the image (compare results of Fig. 2).

is now overlaid by a double heat spot, a minor one at the end of the cat’s body and the main one to the right of the cat’s head, both lying outside the contour of the recognized “poodle”, see Fig. 3(b). Although

in this case the classification is correct, the explanation doesn't make sense at all, because the activation region lies entirely outside the target ("toy poodle"). One could argue that at least the explanation for the "Persian cat" in Fig. 3 (c) has been improved, in comparison to the unchanged image. The hot activation region approaches now the cat's head instead of the paws which is more characteristic of the target. However, a considerable part of the class activation mapping (marked red), still lies beyond the contour of the cat and therefore, at least the position of the recognized target, can be described as not accurate or even wrong. Inception V3 delivers identical results, with respect to changing execution environments, therefore the explanations and classifications of the network are proved to be deterministic under laboratory conditions, that is when no intentional or unintentional perturbations are inserted to the test data.

### 2.3 Xception

In analogy to 2.2, object detections and their explanations calculated with the Xception network are here discussed. In Fig. 4(a) and (b) there are presented the activation heatmaps, produced by the network for the identification of the image regions that correspond to the "dog" ("chow"), and the "cat" respectively, (here identified as "Egyptian cat", whereas Inception V3 identified the cat as a "Tabby cat", compare Fig. 1).

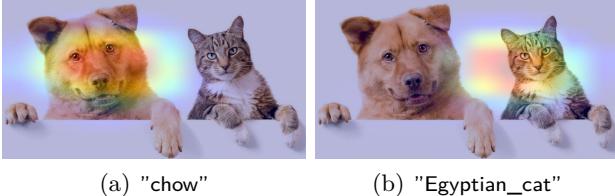


Figure 4. *chow-cat*: Grad-CAM explanations of Xception for the identification of the "chow" (a), in the first place of the top-predictions-list and the "Egyptian cat" (b), in the second place. Third on the list is the "tiger cat" and fourth the "tabby cat". For a comparison, the order of explanations generated by Inception V3 is given in the caption of Fig. 1.

In Fig. 5 the activation maps corresponding to the identification of the "cocker spaniel", the "French bulldog", the "toy poodle" and the "Persian cat" respectively are demonstrated. Similarly to the Inception V3 case, described in the previous section, all prediction scores are almost identical between all HW environment executions. Again, to check the stability of the visual explanations, the identifications of the "cocker

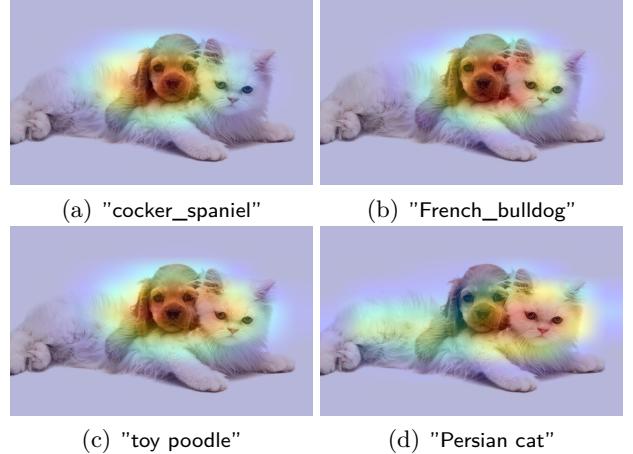


Figure 5. *spaniel-kitty*: Grad-CAM explanations of Xception for the identification of the "cocker spaniel" (a), the "French bulldog" (b), the "toy poodle" (c) and the "Persian cat" (d).

spaniel", the "toy poodle" and the "Persian cat" on the image *spaniel-kitty-paws-cut* have also been tested and the results are depicted in Fig. 6. Xception seems

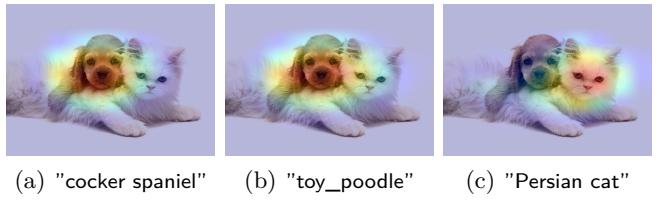


Figure 6. *spaniel-kitty-paws-cut*: Grad-CAM explanations of Xception for the identification of the "cocker spaniel" (a), the "toy poodle" (b) and the "Persian cat" (c) with paws removed from the image (compare Fig. 5).

to consistently focus on the head of the identified animal for the classification and also doesn't produce activation regions outside the contour of the target. The consistency of feature attribution for the explanation and the accuracy of the target position are thus better for Xception in comparison to Inception V3. Because the removal of a part of the image (paws) didn't affect the explanations, at least for the here described experiments, the explanations of Xception can be described as more stable in comparison to the explanations of Inception V3. As far as the definiteness of the classifications and the stability of their scores are concerned, there are following remarks: Xception can unambiguously and correctly distinguish between different classes, focusing on the respective region of the image that depicts the accordingly recognized class. However the differentiation of subclasses within a class, here for

example of dog breeds within the class *dogs*, is neither definite nor stable. For instance, all identifications of the dog races listed in Table 3, produce almost one and the same visual explanation which is close to identical to the explanation for the “cocker spaniel”, on the first place of the top-predictions-list, (see Figs. 6 and 5). This problem probably relates to the quality of *image segmentation* and *fine-grained classification* commonly arising when categories share a number of similar attributes which are also contained within the same bounding box.

Table 3. Xception top-predictions-list for the images *spaniel-kitty* (A) and *spaniel-kitty-paws-cut* (B).

	A	B
1	Cocker spaniel	Cocker spaniel
2	clumber	toy poodle
3	Sussex spaniel	Blenheim spaniel
4	Blenheim spaniel	Pekinese
5	Golden retriever	Chihuahua
6	Pekinese	Sussex spaniel
7	Chow	clumber
8	Toy poodle	Golden retriever
9	Chihuahua	miniature poodle
10	French bulldog	Chow
11	Persian cat	Pomeranian
12	Shih-Tzu	Shih-Tzu
13	Pomeranian	Persian cat

## 2.4 Inception V3 vs. Xception

Explanation properties like correctness, stability, definiteness and accuracy have been already indicated while discussing the images in the previous sections. As already mentioned, Xception appears to have certain advantages in comparison to Inception V3. However, further experiments with both networks, convince that a deeper evaluation should be necessary, if these networks have to be trusted for critical applications. For example in Fig. 7, Inception V3 has identified the “Persian cat” at the seventeenth place on the top-predictions-list but it has also identified a “snowmobile” with a higher probability than that of the cat and a “dog sled”, the latter at the fourth from the top position on the top-predictions-list. The activated image region to explain the “Persian cat” is remarkably similar to the one which explains the “snowmobile”. Puzzling is that for the explanation of the “Persian cat”, the network highlights also a completely irrelevant region in the background of the image, to the right over the head of the “Samoyed dog”. Definiteness and correctness of

the explanations grow rapidly weaker with growing distance from the first score on the top-predictions-list. This well-known problem is obviously critical, especially in case it is necessary to simultaneously classify more than one object categories in one image. It should be stressed, that the here discussed identifications concern objects that belong to the first top-seventeen out of one thousand classes that the network can recognize. The activation regions produced with Inception



Figure 7. *xmas-cat-dog*: Grad-CAM explanations of Inception V3 for the identification of a “dog sled” (a), a “snowmobile” (b) and a “Persian cat” (c). The classification probability decreases from (a) to (c).

V3 for the “Persian cat”, the “snowmobile” and the “dog sled” are to their greatest part overlapping, see Fig. 7. In Fig. 8, Xception’s consistency with regard to the choice of attributes to recognize members of the same class, is demonstrated. It seems to remain robust, also when lower rank scores are explained, as this example of identification of cats shows, with the “Angora” at the twentieth and the “Persian” at the twenty-sixth positions on the top-predictions-list. In Fig. 9, Xcep-

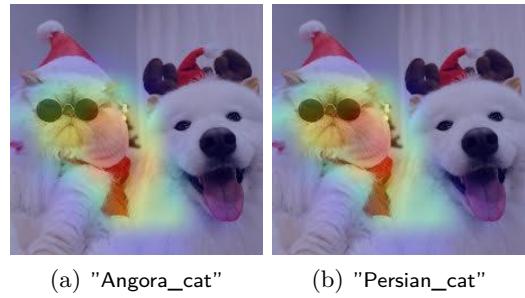


Figure 8. *xmas-cat-dog*: Grad-CAM explanations of Xception for the identification of an “Angora cat” (a) and a “Persian cat” (b).

tion highlights image regions that correspond to the classification of the “Samoyed” (first position), “dog sled” (ninth position) and “Maltese dog” (fourteenth position) on the top-predictions-list. One can see, that the visual activation for the “Samoyed” (a) has much in common with that for the “dog sled” (b), while the explanation for the “Maltese dog”, placed in the gap



Figure 9. *xmas-cat-dog*: Grad-CAM explanations of Xception for the identification of “Samoyed” (a), a “dog sled” (b), and a “Maltese dog” (c). The classification probability decreases from (a) to (c).

between the “Samoyed” and the “Persian cat”, is obviously wrong at least as far as the accuracy of the position of the identified object is concerned and indefinite as regards the class of the object. It is obvious that the consistency of attributes makes hardly any sense without the definiteness of classifications.

### 3 Self-trained Models

The impact of various HW architectures especially on model training will be here investigated after making the source code as deterministic as possible. For the training of the here discussed models, the HW execution environments listed at the end of 2.1 have been employed.

#### 3.1 Deterministic ConvNet

A simple convolutional network (ConvNet) created with `TensorFlow 2` and `Keras` was trained as binary classifier for pictures showing cats and dogs. It consists of alternated `Conv2D` (with `relu` activation) and `MaxPooling2D` layers with five convolutional and four Pooling layers, plus an input and a pre-processing layer, as well as a `Flatten` and a so called `Dense` layer with *sigmoid* activation which ends the model. Flattening is necessary to transform 3D tensor outputs to 1D inputs for the `Dense` layer. The network is described in Listing 3. The image dimension in all test models, `PDIM`, is set to 180. The training data have been taken from the dataset *dogs-vs-cats* provided by a Kaggle competition[36]. A limited number of altogether 2000 images has been used for training and 1000 for the validation of the network, with equal number of cat and dog images. Binary cross entropy was used as loss function for the training together with the `rmsprop` optimizer in its default configuration and as metrics was chosen accuracy. The main task of the network was to create reproducible results, that is to create a

deterministic training process. To this purpose three OS environment variables had to be set first. Using a Jupyter notebook this can be accomplished by a special Jupyter kernel. The setting of the variables reads:

Listing 1. Environment variables set for determinism.

```
PYTHONHASHSEED=1
TF_DETERMINISTIC_OPS=1
TF_CUDNN_DETERMINISTIC=1
```

In the Python code several pseudo-random generators have to be initialized with a *fixed seed*, Python, NumPy, and TensorFlow RNGs are seeded. The according code is as follows:

Listing 2. Pseudo-RNG seeding set for determinism.

```
import numpy as np
import tensorflow as tf

seed = 1001
tf.random.set_seed(seed)
np.random.seed(seed)
random.seed(seed)
```

Because a data augmentation and a dropout-layer have been added to the network to improve accuracy and avoid overfitting, also the seed for the random operations of *flipping*, *rotating* and *zooming* of data has to be set. The resulting network has a total of 991,041 trainable parameters. The reproducibility of the training code of Listing 3 has been tested and could be confirmed for each execution environment separately, by comparing the resulting parameters and accuracy after the completion of each training process. In Listing 4 and Listing 5 the accuracy and a number of corresponding network weights which belong to the first and to the last but one layers of the model are displayed, as calculated in the HW-1 and HW-2 environments, respectively, after 90 epochs of training. Although the accuracies in the two execution environments are almost identical, the calculated parameters are completely different, which shows that each environment causes the model to converge to a different optimization minimum.

#### Deterministic ConvNet Summary

- Number of layers: 12
- Trainable parameters: 991,041
- Training times:
  - HW-1: ca. 2 s / epoch
  - HW-3: ca. 3 s / epoch
  - HW-4: ca. 20 s / epoch
  - HW-5: ca. 22 s / epoch

The deterministic ConvNet was developed as a proof of concept and it is by no means an optimized model.

Listing 3. Deterministic ConvNet.

```

data_augmentation = keras.Sequential([
    kl_exp_prepoc.RandomFlip("horizontal", seed=1),
    kl_exp_prepoc.RandomRotation(0.1, seed=1),
    kl_exp_prepoc.RandomZoom(0.2, seed=1),])

PDIM = 180
inputs = keras.Input(shape=(PDIM, PDIM, 3))
x = data_augmentation(inputs)
x = keras.layers.experimental.preprocessing.Rescaling(1./255)(x)
x = keras.layers.Conv2D(filters=32, kernel_size=3, activation="relu")(x)
x = keras.layers.MaxPooling2D(pool_size=2)(x)
x = keras.layers.Conv2D(filters=64, kernel_size=3, activation="relu")(x)
x = keras.layers.MaxPooling2D(pool_size=2)(x)
x = keras.layers.Conv2D(filters=128, kernel_size=3, activation="relu")(x)
x = keras.layers.MaxPooling2D(pool_size=2)(x)
x = keras.layers.Conv2D(filters=256, kernel_size=3, activation="relu")(x)
x = keras.layers.MaxPooling2D(pool_size=2)(x)
x = keras.layers.Conv2D(filters=256, kernel_size=3, activation="relu")(x)
x = keras.layers.Flatten()(x)
x = keras.layers.Dropout(0.5, seed=7001)(x)
outputs = keras.layers.Dense(1, activation="sigmoid")(x)
model = keras.Model(inputs=inputs, outputs=outputs)
model.compile(loss="binary_crossentropy", optimizer="rmsprop", metrics=["accuracy"])

```

Listing 4. ConvNet on HW-1: Deterministic training results.

```

Out: accuracy: 0.849

In : model_weights[0][:,:,0,0]
Out: <tf.Tensor: shape=(3, 3), dtype=float32, numpy=
      array([[-0.00111067, -0.08925765, -0.03877171],
             [ 0.06882513,  0.07853891, -0.07341643],
             [-0.10082538,  0.05409119, -0.11010181]], dtype=float32)>

In : model_weights[-2][:32,0]
Out: <tf.Tensor: shape=(32,), dtype=float32, numpy=
      array([ 0.02049963, -0.06807294,  0.01771718,  0.00662495,  0.09211864,
             0.03866815,  0.05907019,  0.00925133,  0.02810607, -0.00849974,
             0.0199494 ,  0.01444575, -0.07486248, -0.05971878, -0.04888046,
             0.05762889, -0.114383 , -0.03059661, -0.00386733,  0.04686596,
             0.11158869, -0.00510099, -0.01760828,  0.00915093,  0.06470113,
             0.02472718, -0.17019744, -0.06843327,  0.11263403, -0.05122007,
             -0.02696232,  0.01008716], dtype=float32)>

```

Therefore, the reproducibility of its Grad-CAM explanations but not their quality, are tested here. Classification explanations calculated here for a test image showing a Chow-Chow dog (image taken from [11]) are depicted for two different execution environments in Fig. 10 and Fig. 11, respectively. The visual explanations remain stable (are reproducible) within each execution environment but they are, quite like the classification results, environment dependent. The quality of the classifications is not the object of investigation for these simple, first deterministic models.

### 3.2 Deterministic mini Xception

A *small* version of Xception, the *mini Xception-like* of Chollet [10], has been chosen to be modified, so as

to make its training deterministic. The system configurations described in the previous section (Listings 1 and 2), and the seed settings for the data augmentation had to be applied also in this case. A couple of additional steps are however also necessary. The original model definition is as given in [10]. The final version of the code, made deterministic for CPU environments, is displayed in Listing 6. The model counts 718,849 trainable parameters (while the corresponding number given in [10] is actually the number of total parameters). To enhance the layer function's determinism, the parameters `depthwise_initializer` and the `pointwise_initializer` of the `SeparableConv2D` are set explicitly to the `glorot_uniform` initializer with a fixed seed. The same change is applied to the `kernel_initializer` in the function `Conv2D`. This code

Listing 5. ConvNet on HW-2: Deterministic training results.

```

Out: accuracy: 0.836

In: model_weights[0][:,:,0,0]
Out: <tf.Tensor: shape=(3, 3), dtype=float32, numpy=
array([[-0.02197945, -0.11502645, -0.06399402],
       [ 0.06629982,  0.07693411, -0.07907421],
       [-0.08929715,  0.07290921, -0.10029382]], dtype=float32)>

In: model_weights[-2][:32,0]
Out: <tf.Tensor: shape=(32,), dtype=float32, numpy=
array([-0.13660763,  0.08144909,  0.0058543 , -0.02693423,  0.02785763,
       0.16917986, -0.00647367, -0.00365615, -0.01310152,  0.04297437,
       0.00301503,  0.01947881, -0.09520608, -0.05354575, -0.06465469,
       0.01503169, -0.06535202, -0.06438911,  0.07274752, -0.01518494,
       -0.04213503,  0.0165184 , -0.04465574, -0.003416 , -0.09923518,
       -0.00701612, -0.05580736,  0.06382342,  0.07347441, -0.06864858,
       -0.05487159, -0.01903648], dtype=float32)>

```

Listing 6. mini Xception: Deterministic (on CPU) training code.

```

init_glorot_u = tf.keras.initializers.glorot_uniform

inputs = keras.Input(shape=(PDIM, PDIM, 3))
x = data_augmentation(inputs)
x = keras.layers.experimental.preprocessing.Rescaling(1./255)(x)
x = keras.layers.Conv2D(filters=32, kernel_size=5, use_bias=False,
                      kernel_initializer=init_glorot_u(seed=1))(x)

for size in [32, 64, 128, 256, 512]:
    residual = x
    x = keras.layers.BatchNormalization()(x)
    x = keras.layers.Activation("relu")(x)
    x = keras.layers.SeparableConv2D(size, 3, padding="same", use_bias=False,
                                    depthwise_initializer=init_glorot_u(seed=1),
                                    pointwise_initializer=init_glorot_u(seed=2))(x)
    x = keras.layers.BatchNormalization()(x)
    x = keras.layers.Activation("relu")(x)
    x = keras.layers.SeparableConv2D(size, 3, padding="same", use_bias=False,
                                    depthwise_initializer=init_glorot_u(seed=1),
                                    pointwise_initializer=init_glorot_u(seed=2))(x)
    x = keras.layers.MaxPooling2D(3, strides=2, padding="same")(x)
    residual = keras.layers.Conv2D(size, 1, strides=2, padding="same", use_bias=False,
                                 kernel_initializer=init_glorot_u(seed=1))(residual)
    x = keras.layers.add([x, residual])

    x = keras.layers.GlobalAveragePooling2D()(x)
    x = keras.layers.Dropout(0.5, seed=7001)(x)
outputs = keras.layers.Dense(1, activation="sigmoid")(x)
model = keras.Model(inputs=inputs, outputs=outputs)
model.compile(loss="binary_crossentropy", optimizer="rmsprop", metrics=["accuracy"])

```

is reproducible when executed in CPU environments without graphical support. Runtimes of the deterministic code for HW-2 are given in Table 4. Switching off

Table 4. Deterministic mini Xception on HW-2

Single-thread	Multi-thread
ca. 330 s / Epoch	ca. 52 s / Epoch

parallelism of Tensorflow can be achieved by using the

instructions given in Listing 7.

However, these instructions to turn off multi-threading had no practical effect, when applied in the GPU environment. It was indeed not possible to make the GPU work in single-thread mode. To make mini Xception deterministic for GPU environments, two changes are necessary in the code listed in Listing 6 which actually change the network:

1. replace `SeparableConv2D` by `Conv2D`,

Listing 7. Switching off parallelism of Tensorflow.

```
tf.config.threading.set_inter_op_parallelism_threads(1)
tf.config.threading.set_intra_op_parallelism_threads(1)
```



(a) 88 % Chow

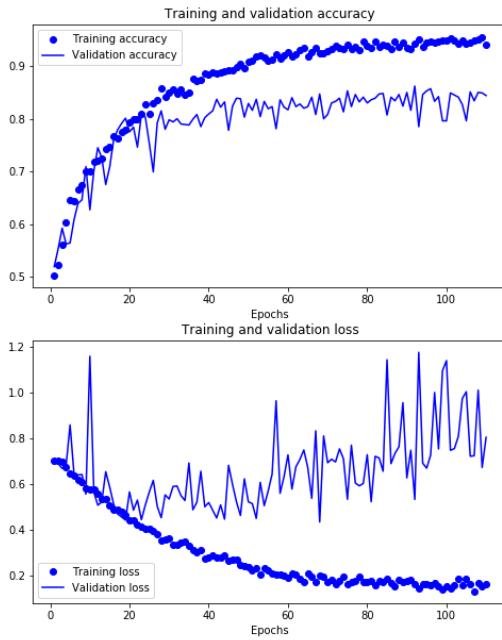


Figure 10. Deterministic ConvNet on HW-1: Grad-CAM explanation of the *right* identification of the “Chow” (a), model’s accuracy and validation loss curves (b).

- remove the line containing `keras.layers.add()`.

The in this way resulting deterministic model however, has little in common with the original mini Xception.

## Mini Xception Summary

- Number of layers: 44
- Trainable parameters: 718,849



(a) 76 % Cat

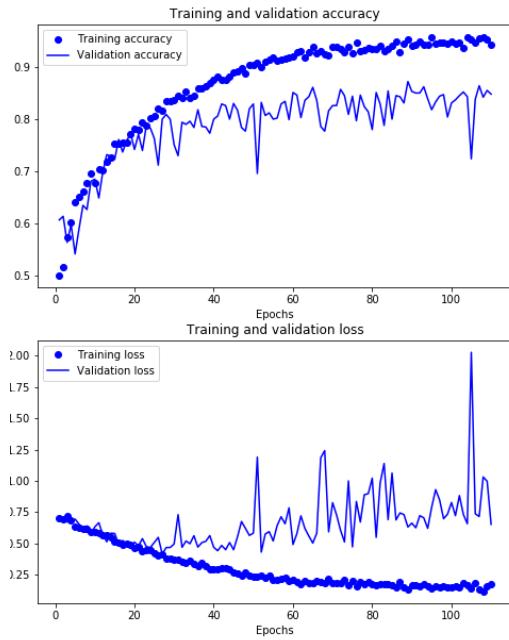


Figure 11. Deterministic ConvNet on HW-2: Grad-CAM explanation of the *false* classification of the “Chow” as a “Cat” (a), model’s accuracy and validation loss curves (b).

- Training times:
  - HW-2: ca. 52 s / epoch  
(to compare: single thread 330 s / epoch)
  - HW-4: ca. 54 s / epoch
  - HW-5: ca. 56 s / epoch

For a comparison: on HW-1, the non-deterministic

training takes ca. 18 s per epoch. The deterministic mini Xception was developed as a proof of concept. Tests of the Grad-CAM explainability of the network’s classifications have also been performed. In Fig. 12 and Fig. 13 there are depicted the visual explanations of the model, as well as the training and validation loss curves respectively, after 100 epochs of training in two different execution environments. The visual explanations remain stable (are reproducible) within each execution environment but they are, quite like the classification results, environment dependent. The Grad-CAM process code used in this work is as given in Section 9.4.3 of [10].

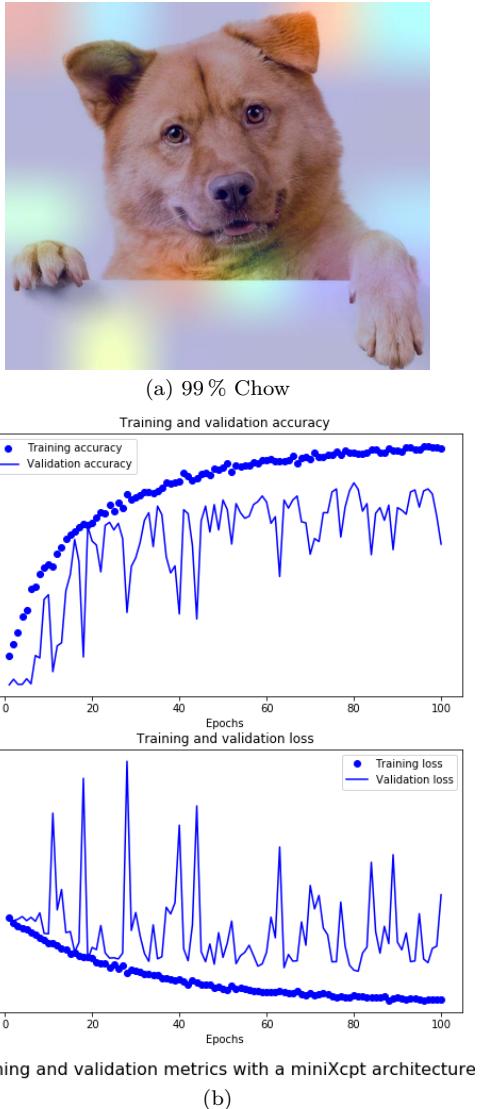


Figure 12. Deterministic Mini Xception on HW-2: Grad-CAM explanation of the *correct* classification as “Chow” (a), model’s accuracy and validation loss curves (b).



(a) 100 % Cat

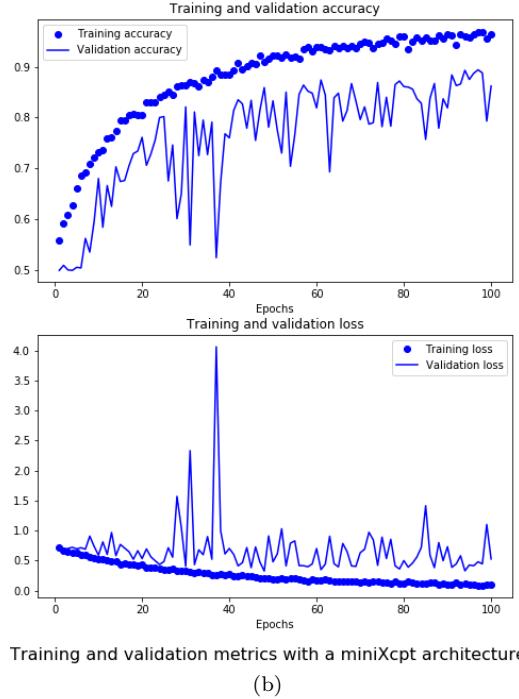


Figure 13. Deterministic Mini Xception on HW-5: Grad-CAM explanation of the *false* object classification as “Cat” (a), model’s accuracy and validation loss curves (b).

## 4 Conclusions and future work

In this work, the non-reproducibility of the training of DL models in association with the employment of different HW environments (with and without GPU) for the execution of the source code, has been discussed. The non-reproducibility of models, necessary implies the non-reproducibility of the explanations of their results, the quality of which is of vital importance, given the increasing dependency on ML for decision making in many sectors of life, like automotive, telecommunications, healthcare etc. Aside from the nondeterminism of training algorithms, core libraries like TensorFlow, CNTK, Theano, Pytorch and low-level libraries like

for example cuDNN, are known to exhibit a so-called *implementation-level* variance across all their evaluated versions [16]. That means that even if the variance introduced by algorithmic factors like shuffled batch ordering, dropout regularization, data augmentation etc. becomes eliminated by using fixed random seeds, the core implementation variance will still be added to the results. The development of deterministic code for two different CNN model architectures has been successfully achieved. This has been confirmed with test runs under the condition that the code is executed on similar CPU environments with no use of graphic card support (here: AMD Zen architecture with identical number of cores). Additionally, the first of the models, the deterministic ConvNet, runs deterministically also with activated graphic card support. The technical steps towards the creation of these results are described in detail. The code used and instructions are listed. Using the Grad-CAM method, HW-dependent reproducible model classifications and their according reproducible explanations have been visually demonstrated for both models. The two prototype networks have not been optimized in any way. The number of training epochs, the training and validation metrics are arbitrary. If they should be further optimized, each optimization step has to be rendered reproducible too. Earlier performed tests had confirmed that the ready-trained Inception V3 and Xception models deliver HW-independent and reproducible results, whereby the results of the two models are different. It is well-known that DL models undergo further optimization stages after the end of their training and before they reach their final form. For example, ensemble techniques are used to teach a model how to average or combine predictions of multiple models. These steps are mostly intransparent and hardly reproducible too [18, 6, 4, 32]. Reproducibility is essential also in the context of fault tolerance, iterative refinement, debugging and optimization of adaptable models, especially for large scale and distributed workflow applications, like cloud computing platforms and Industry 4.0 [15]. The need for specific fault tolerance features for the properties of DL algorithms and their implementations has been already discussed elsewhere [2, 35, 33]. Reproducibility is also the basis for developing comparison criteria and metrics for the objective evaluation of model properties, like robustness and trustworthiness [16, 23]. Visual model explanations are helpful for humans to create insights from data information but they are seldom unique, they are often non-intuitive or not consistent, as regards the selected features for the explanation. Moreover, DL models and their explanations are vulnerable to errors, for instance when slightest perturbations are introduced to the input image [19]. In addition, visual explanations don't make transparent how networks produce predictions, why gradients converge etc. [43]. The reproducibility of ML training is expected to boost developments in XAI, with the scope to

finally create humanly comprehensible, causal interpretations of decisions produced by complex DL models. There exist no globally accepted measures of accuracy or correctness for ML models, hence there is a need for a mathematical formalism to describe properties, which models should prove to have and how to evaluate them. Approaches to an *axiomatic formulation* of attribute-based predictions of DL networks, propose model properties with respect to the input-data features that must be fulfilled. As such, there have been named: completeness, sensitivity, linearity, symmetry, continuity and implementation invariance [40]. For the future, it is intended to integrate some of these properties as boundary conditions in model implementations, which will have to be satisfied throughout the training process. An investigation, if additional restrictions to the model can positively contribute to the model's reproducibility seems worth trying. Implementation invariance is satisfied when two functionally equivalent networks find identical attributions for the same input image and baseline image [30]. This work shows that a single implementation can be functionally non-equivalent to itself, if executed in different HW environments. Future attempts to alleviate this condition should not completely disregard the investigation of also open architectures and standards for graphic cards.

## References

- [1] A. Abid. How to Solve ML's Reproducibility Crisis in 3 Easy Steps, 2021. Posted on [towardsdatascience.com](https://towardsdatascience.com/addressing-mls-reproducibility-crisis-7d59e9ed050) <https://towardsdatascience.com/addressing-mls-reproducibility-crisis-7d59e9ed050> (accessed Nov. 2021). 2
- [2] V. Amatya, A. Vishnu, C. Siegel, and J. Daily. What does fault tolerant deep learning need from MPI? In *Proceedings of the 24th European MPI Users' Group Meeting*, pages 1–11, 2017. doi:[10.1145/3127024.3127037](https://doi.org/10.1145/3127024.3127037). 13
- [3] A. Beam, A. Manrai, and M. Ghassemi. Challenges to the Reproducibility of Machine Learning Models in Health Care. *JAMA*, 323:305–306, 2020. doi:[10.1001/jama.2019.20866](https://doi.org/10.1001/jama.2019.20866). 2
- [4] D. Borisenko. Ensembles: the only (almost) free Lunch in Machine Learning, 2020. Posted on [towardsdatascience.com](https://towardsdatascience.com) <https://towardsdatascience.com/ensembles-the-almost-free-lunch-in-machine-learning-91af7ebe5090> (accessed Nov. 2021). 13
- [5] D. Britz. AI Research, Replicability and Incentives, 2020. Posted on [dennybritz.com](https://dennybritz.com) <https://dennybritz.com/blog/ai-replication-incentives/> (accessed Nov. 2021). 1
- [6] J. Brownlee. Ensemble Learning Methods for Deep Learning Neural Networks, 2019. Posted on [machinelearningmastery.com](https://machinelearningmastery.com)

- <https://machinelearningmastery.com/ensemble-methods-for-deep-learning-neural-networks/> (accessed Nov. 2021). 13
- [7] J. Brownlee. A Tour of Machine Learning Algorithms, 2020. Posted on machinelearningmastery.com <https://machinelearningmastery.com/a-tour-of-machine-learning-algorithms/> (accessed Nov. 2021). 2
- [8] J. Brownlee. Why Do I Get Different Results Each Time in Machine Learning?, 2020. Posted on machinelearningmastery.com <https://machinelearningmastery.com/different-results-each-time-in-machine-learning/> (accessed Nov. 2021). 2
- [9] F. Chollet. Xception: Deep Learning with Depthwise Separable Convolutions. [arXiv:1610.02357](https://arxiv.org/abs/1610.02357), 2017. 3, 4
- [10] F. Chollet. *Deep Learning with Python*, chapter Advanced deep learning for computer vision, pages 238–279. Manning Publ. Co., 2nd edition, 2021. ISBN: 9781617296864. 9, 12
- [11] F. Chollet. Grad-CAM class activation visualization, 2021. Code example on keras.io [https://keras.io/examples/vision/grad\\_cam/](https://keras.io/examples/vision/grad_cam/) (accessed Nov. 2021). 2, 9
- [12] B. Dickson. The untold story of GPT-3 is the transformation of OpenAI, 2020. Posted on bdtechtalks.com <https://bdtechtalks.com/2020/08/17/openai-gpt-3-commercial-ai/> (accessed Nov. 2021). 2
- [13] Z. Ding, A. Reddy, and A. Joshi. 5 – Reproducibility. Reproducibility Crisis in Science and ML, 2020. Posted on blog.ml.cmu.edu <https://blog.ml.cmu.edu/2020/08/31/5-reproducibility/> (accessed Nov. 2021). 1
- [14] L. Engstrom, A. Ilyas, S. Santurkar, D. Tsipras, F. Janoos, L. Rudolph, and A. Madry. Implementation Matters in Deep Policy Gradients: A Case Study on PPO and TRPO, 2020. ICLR 2020 Conference: <https://openreview.net/forum?id=r1etN1rtPB> (accessed Nov. 2021). 1
- [15] G. N. et al. Machine Learning and Deep Learning frameworks and libraries for large-scale data mining: a survey. *Artif. Intell. Rev.*, 52:77–124, 2019. doi:10.1007/s10462-018-09679-z. 13
- [16] H. P. et al. Problems and Opportunities in Training Deep Learning Software Systems: An Analysis of Variance. In *2020 35th IEEE/ACM International Conference on Automated Software Engineering (ASE)*, pages 771–783, 2020. IEEE Xplore <https://ieeexplore.ieee.org/document/9286042>. 13
- [17] J. P. et al. Improving Reproducibility in Machine Learning Research (A Report from the NeurIPS 2019 Reproducibility Program). [arXiv:2003.12206](https://arxiv.org/abs/2003.12206), 2020. 1
- [18] R. L. et al. Deep Convolutional Neural Networks With Ensemble Learning and Generative Adversarial Networks for Alzheimer’s Disease Image Data Classification. *Front. Aging Neurosci.*, 13:720226, 2021. doi:10.3389/fnagi.2021.720226. 13
- [19] I. Goodfellow, J. Shlens, and C. Szegedy. Explaining and Harnessing Adversarial Examples. Published at *International Conference on Learning Representations 2015* [arXiv:1412.6572](https://arxiv.org/abs/1412.6572), 2015. 13
- [20] O. Gundersen and S. Kjensmo. State of the Art: Reproducibility in Artificial Intelligence. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 32, 2018. URL: <https://ojs.aaai.org/index.php/AAAI/article/view/11503>. 1
- [21] K. He, X. Zhang, S. Ren, and J. Sun. Deep Residual Learning for Image Recognition. In *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 770–778, 2016. 3
- [22] W. Heaven. The way we train AI is fundamentally flawed, 2020. Posted on technologyreview.com <https://www.technologyreview.com/2020/11/18/1012234/training-machine-learning-broken-real-world-health-nlp-computer-vision/> (accessed Nov. 2021). 3
- [23] B. Heil, M. Hoffman, F. Markowitz, S.-I. Lee, C. Greene, and S. Hicks. Reproducibility standards for machine learning in the life sciences. *Nat. Methods*, 18:1132–1135, 2021. doi:10.1038/s41592-021-01256-7. 1, 13
- [24] P. Hemant. Reproducible Machine Learning, 2020. Posted on towardsdatascience.com <https://towardsdatascience.com/reproducible-machine-learning-cf1841606805> (accessed Nov. 2021). 2
- [25] M. Hobbahn. The reproducibility crisis in Machine Learning, 2020. Posted on mariushobbahn.com [https://www.mariushobbahn.com/2020-03-22-case\\_for\\_rep\\_ML/](https://www.mariushobbahn.com/2020-03-22-case_for_rep_ML/) (accessed Nov. 2021). 1
- [26] M. Hutson. Artificial intelligence faces reproducibility crisis. *Science*, 359(6377):725–726, 2018. doi:10.1126/science.359.6377.725. 1
- [27] M. Hutson. Missing data hinder replication of artificial intelligence studies, 2018. doi:10.1126/science.aat3298. 1
- [28] A. Irpan. Deep Reinforcement Learning Doesn’t Work Yet, 2018. Posted on alexirpan.com <https://www.alexirpan.com/2018/02/14/r1-hard.html> (accessed Nov. 2021). 1
- [29] R. Islam, P. Henderson, M. Gomrokchi, and D. Precup. Reproducibility of Benchmarked Deep Reinforcement Learning Tasks for Continuous Control, 2017. ICML 2017, Reproducibility in ML Workshop: <https://openreview.net/forum?id=BJNuErQX-> (accessed Nov. 2021). 1
- [30] R. Khandelwal. Understanding Deep Learning Models with Integrated Gradients, 2020. Posted on towardsdatascience.com <https://towardsdatascience.com/integrated-gradients-101-104a2a2a2a>. 1

- [com/understanding-deep-learning-models-with-integrated-gradients-24ddce643dbf](https://com/understanding-deep-learning-models-with-integrated-gradients-24ddce643dbf) (accessed Nov. 2021). 13
- [31] K. Khetarpal, Z. Ahmed, A. Cianflone, R. Islam, and J. Pineau. RE-EVALUATE: Reproducibility in Evaluating Reinforcement Learning Algorithms, 2018. ICML 2018, Reproducibility in ML Workshop: <https://openreview.net/forum?id=HJgAmITcgm> (accessed Nov. 2021). 1
- [32] S. Mall. Reproducibility in Machine Learning – Research and Industry, 2019. Posted on suneeta-mall.github.io <https://suneeta-mall.github.io/2019/12/21/Reproducible-ml-research-n-industry.html> (accessed Nov. 2021). 1, 13
- [33] L. Myllyaho, M. Raatikainen, T. Männistö, J. Nurminen, and T. Mikkonen. On misbehaviour and fault tolerance in machine learning systems. *J. Syst. Softw.*, 183:111096, 2022. doi:[10.1016/j.jss.2021.111096](https://doi.org/10.1016/j.jss.2021.111096). 13
- [34] J. Pineau, K. Sinha, G. Fried, R. Ke, and H. Larochelle. ICLR Reproducibility Challenge 2019. *ReScience C*, 5(2):#5, 2019. doi:[10.5281/zenodo.3158244](https://doi.org/10.5281/zenodo.3158244). 1
- [35] S. Prathibha. Investigating the Performance of Machine Learning Algorithms for Improving Fault Tolerance for Large Scale Workflow Applications in Cloud Computing. In *2019 International Conference on Computational Intelligence and Knowledge Economy (ICCIKE)*, pages 187–190, 2019. doi:[10.1109/ICCIKE47802.2019.9004379](https://doi.org/10.1109/ICCIKE47802.2019.9004379). 13
- [36] M. Research. Dogs vs. Cats dataset, 2013. Kaggle competition, published by Microsoft Research for non-commercial research purposes, available at <https://www.kaggle.com/c/dogs-vs-cats/data> (accessed Jan. 2021). 8
- [37] R. Selvaraju, M. Cogswell, A. Das, R. Vedantam, D. Parikh, and D. Batra. Grad-CAM: Visual Explanations from Deep Networks via Gradient-Based Localization. In *2017 IEEE International Conference on Computer Vision (ICCV)*, pages 618–626, 2017. doi:[10.1109/ICCV.2017.74](https://doi.org/10.1109/ICCV.2017.74). 2
- [38] K. Sinha, J. Pineau, J. Forde, R. Ke, and H. Larochelle. NeurIPS 2019 Reproducibility Challenge. *ReScience C*, 6(2):#11, 2020. doi:[10.5281/zenodo.3818627](https://doi.org/10.5281/zenodo.3818627). 1
- [39] E. Strubell, A. Ganesh, and A. McCallum. Energy and Policy Considerations for Deep Learning in NLP. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 3645–3650, 2019. doi:[10.18653/v1/P19-1355](https://doi.org/10.18653/v1/P19-1355). 2
- [40] M. Sundararajan, A. Taly, and Q. Yan. Axiomatic Attribution for Deep Networks. [arXiv:1703.01365](https://arxiv.org/abs/1703.01365), 2017. 13
- [41] C. Szegedy, S. Ioffe, V. Vanhoucke, and A. Alemi. Inception-v4, Inception-ResNet and the Impact of Residual Connections on Learning. In *AAAI'17: Proceedings of the Thirty-First AAAI Conference on Artificial Intelligence*, pages 4278–4284, 2017. doi:[10.5555/3298023](https://doi.org/10.5555/3298023). 3
- [42] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna. Rethinking the Inception Architecture for Computer Vision. In *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 2818–2826, 2016. doi:[10.1109/CVPR.2016.308](https://doi.org/10.1109/CVPR.2016.308). 3
- [43] A. Taly. Explaining machine learning models, 2019. Slides available: <http://theory.stanford.edu/~ataly/Talks/ExplainingMLModels.pdf> (accessed Nov. 2021). 13
- [44] S.-H. Tsang. Review: Xception — With Depthwise Separable Convolution, Better Than Inception-v3 (Image Classification), 2018. Posted on towardsdatascience.com <https://towardsdatascience.com/review-xception-with-depthwise-separable-convolution-better-than-inception-v3-image-dc967dd42568> (accessed Nov. 2021). 3
- [45] J. Villa and Y. Zimmerman. Reproducibility in ML: why it matters and how to achieve it, 2018. Posted on determined.ai <https://www.determined.ai/blog/reproducibility-in-ml> (accessed Nov. 2021). 2
- [46] P. Warden. The Machine Learning Reproducibility Crisis, 2018. Posted on blog.dominodatalab.com <https://blog.dominodatalab.com/machine-learning-reproducibility-crisis> (accessed Nov. 2021). 2