Effectiveness of adversarial examples on class-imbalanced Convolutional Neural Networks

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Abstract. Image recognition and machine learning have been one of the most fast paced fields of Artificial Intelligence. A considerable amount of literature was published on the performance of Convolutional Neural Networks and the field has evolved considerably in the last years. However, as most machine learning methods, these networks suffer from the data imbalance problem. When the underlying training dataset is comprised of unequal number of samples for each label/class. Such difference naturally causes a phenomenon known as domain shift, which can be explained by the low generalisation capabilities of a model when presented with previously unseen data. Recent research have focused on a technique called Gradient Sign that forces domain shift on deep networks by creating adversarial examples. These are usually comprised of small directed changes on original data points that causes inputs to be misclassified by the predictive algorithm. Recent developments in such methods have heightened the need for better of understanding of this phenomena. This study focuses on an experimental approach that sheds light on the link between the imbalanced learning problem and adversarial examples. Through a series of experiments we try to find intuitive explanations behind the success of gradient sign methods and we evaluate their effectiveness against models trained on imbalanced datasets

Keywords: convolutional neural networks, adversarial examples, gradient sign, imbalanced training the abstract section

1 Motivation

Convolutional Networks are a class of deep learning algorithms that can use many layers of nonlinear or linear processing in cascade for feature extraction and transformation. They are still very similar to ordinary Neural Networks (made up of neurons that have learnable weights and biases). However, such algorithms makes the explicit assumption that the inputs are images and, therefore, are based on learning abstract representations of data with spatial properties [4].

Until recently, these networks were known for having high generalisation capabilities, however, methods using the internal model information were proven to successfully reduce their performance by creating inputs known as Adversarial Examples [6].

Adversaries can successfully force domain shift in such a way that the model becomes unable to generalise well on perturbed samples. Since training data in most circumstances can not cover the entire feature space, the real decision boundary of a classification model generally becomes more complex as the phenomenon becomes more nuanced and the feature and dimension space becomes larger [1]. This can be exploited by adversaries through the use of the model error as a guideline for perturbing a sample that can successfully cause a misclassification of the input by the targeted system.

Besides the near human performance of deep convolutional neural networks, adversaries are still capable of forcing domain shift on classes with overlapping or similar distributions. This problem could then become critical when these adversaries are used to attack models where the training data has a large variance on the number of samples per class.

2 Related Work

Recent work has shown that the generalisation capabilities of deep networks is rather sparse [11], [13]. Thus, there is an opportunity for methods to exploit empty pockets of space and, hence, systematically create an adversary that produces an incorrect, high confidence prediction for an image without visible distortion. This can be done by adding just enough intentional noise to each pixel of the image so as to fool an algorithm into thinking that the image has an incorrect label [6], [11], [13], [16]. The resulting outcome of these methods are known as Adversarial Examples.

The Gradient Sign method developed by Goodfellow et al. (2014) has been used as the foundation of many of the experiments in adversarial crafting. The results have shown that DNNs can possibly have linear behavior in very high dimensional spaces. Most inputs were miss-classified not only on Goodfellow et. al [6] experiments but many others [3],[11],[14].

Developing robustness to adversarial examples has been approached many times as academic work, recent research [14] has shown that one can use transfer learning [17] to perform black-box attacks against Deep Neural Networks.The combination of adversaries and transfer learning creates a threat vector for many state of the art methods. Attacks can, however, depend on some specific information of the target [13]. As most recent applied methods depend on the network gradient information, there is a straight dependence on the network confidence per class label and the robustness of the model to adversarial attacks.

Imbalanced learning is a well known cause for lower performance of several machine learning algorithms [7], [9]. Data distribution on real world is often skewed and rarely contains enough information to learn all the required features of the data domain. As the dependency of specific class labels grows, the vulnerability of the system increases as wrong predictions of the critical label could lead to unwanted outcomes. Adversaries are proven to explore class distributions vicinities, and the question whether imbalanced training sets affects them is still unanswered.

This work presents an experimental approach aimed on the understanding of the factors leading to robustness to adversarial attacks on class imbalanced convolutional neural networks. Through the use of the Fast Gradient Sign Method we investigate how a skewed data distribution could affect the network resilience to such attacks. The understanding of such threat vectors is of the utmost importance for the development of current techniques, as it drives the creation of new regularisation techniques.

3 Initial Setup

For the purposes of this work, we aimed to use a dataset that could not only be visually rich but also could facilitate analysis between different class labels. The 2014 ImageNet dataset [5] would be the natural choice, however, the amount of classes would make it harder to make comparisons, as the number of classes is around 1,000. We use a dataset with similar characteristics, the CIFAR-10 [10]. It contains 10 different class labels of 32x32 images, which makes it easier to train our algorithm from scratch and also to understand deeper relationships between class labels.

3.1 Network Architecture

In terms of network architecture, we looked into the ILSVRC competition for the highest performers.From all networks tested on Canziani et al (2016) [4], the VGG16-19 from Simonyan et al. (2014) [15] seemed to have the best trade off between accuracy and performance (inference time). The VGG architecture won the first and second places on the ILSVRC-2014 submission on the localisation and classification task.The main contribution of the VGG network was showing that the depth of the network is a critical component for good classification performance. The model can be assembled with 16 or 19 Conv/FC layers and it features an extremely homogenous architecture that only performs 3x3 convolutions and 2x2 pooling from beginning to end.

The design of the VGG16 has been proven to work even on datasets with several classes that are very different from each other. As the dataset used in this work has only 10 classes, the two FC-4096 layers were replaced by one single layer with 512 neurons and RELU activations. In addition, the total number of convolutions blocks and pooling were reduced to 3, with the first layer having 2 stacked convolution layers followed by a max pooling of stride 2x2 and the last two layers with 3 stacked convolutions also followed by a max pooling of stride 2x2. Since CIFAR-10 images are only 32x32, the original VGG16 architecture would end up having an output of shape of only 1x1 pixel at the last layer. In order to avoid this problem, the number of layers were reduced so to fit our dataset domain

3.2 Training Parameters

The optimisation technique used in this work was developed by Bengio (2015) [2], namely RMSProp. This method is an adaptive learning rate scheme that can take the absolute values of the Hessian's eigenvalues and, therefore, approximate the equilibration pre-conditioner. As shown on Bengio's work [2], the method outperforms current SGD methods by achieving convergence faster.The learning rate for the method was set at 10^{-4} and the decay 10^{-5}.

Our architecture was trained until no more reasonable changes δ were detected in the validation loss so we could dismiss unnecessary training steps and consequently any kind of over-fitting. This was achieved by using the Early Stopping technique with a δ of 10^{-4}. For instance, training would be stopped if no improvement over the specified δ was seen for 10 steps in a row.The results on the full dataset are shown on figure 1.

3.3 Gradient Sign methods

The Gradient Sign is an exploitation of the loss function in an optimization process so one can maximize any class score for a given input image [14]. Since everything in a ConvNet is differentiable it is relatively straight forward to compute the gradient information of any specific class of the input domain. Basically we choose an output and we apply the reshaped gradient computation of that class to our input using equations 1 or 2.

Adding or subtracting noise from images will generate different adversaries. Supposed we choose the same class gradient, adding noise δ to an image, one would be making the gradient to go "uphill" and therefore moving away from the class, this results in an increase in value of the loss function and thus should be referred as the Ascent Method. On the other hand, when moving the opposite direction (down), one would be doing a process similar to the optimization of a loss function where we approach the minimum of a function and, thus, we get closer to the desired class, this approach is hereby known as the Descent Method. When applying the perturbation we are only interested in the direction of the gradient and not its magnitude, therefore, we take the sign of the gradient and we control its magnitude through the ϵ parameter. Equations 1 and 2 are respectively for the ascent and descent perturbations described in this section.

$$C(x+\delta) \approx C(x) + \epsilon * sign(\nabla C) \tag{1}$$

$$C(x+\delta) \approx C(x) - \epsilon * sign(\nabla C) \tag{2}$$

Perturbations could be applied once or many times in order to successfully create an adversary. When only one iteration of perturbations is applied, we call the method FGSM (Fast Gradient Sign Method). On the other hand, applying the same perturbation many times is known as IGSM (Iterative Gradient Sign Method) [6]. The latter could always end up into changing the classification output as it can be seen as taking small steps into the direction of our ∇C.

3.4 Backpropagated Class Gradient

The choice of the backpropagated class gradient has direct influence on the generated adversary. For instance, one could select a specific class as the target of a perturbation but this would ultimately introduce undesirable variance when crafting adversaries for our experiment, as each class could have different effects within our target and, thus, the perturbation could be different on each case. In order to address this problem, we have chosen the class itself as the backpropagated gradient coupled with the ascent method. The intuition behind this choice is that we look to increase the cost function of the target class by moving away from the current label.

For all classes, the amount of change on each pixel needed to be carefully chosen as we did not want to change an image too much to a point where it would be unrecognizable to human perception. Moreover, in order to test our networks, we needed an ϵ value that would provide only the minimum amount of perturbation to all classes so as to push most of the samples to the closest vicinity leading to a successful misclassification. From all the trials performed, the value of ϵ that seemed to fulfill our needs was 0.01.

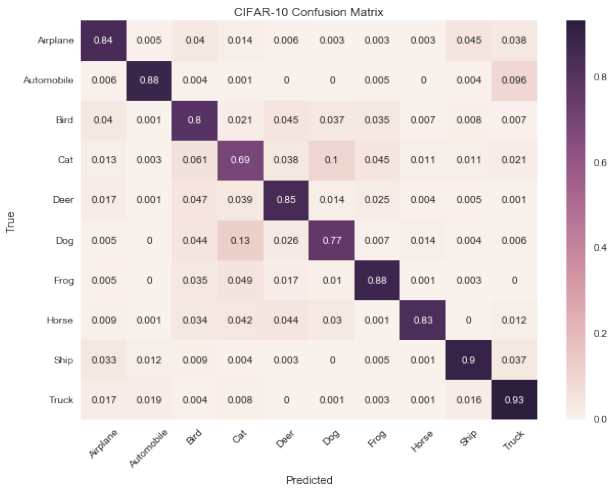


Fig. 1. Results of our adapted VGG architecture on CIFAR-10 dataset

3.5 Same and Different model perturbations

Another important choice was regarding which trained network would serve as the baseline for our gradient calculation. We have generated perturbation using two different networks on each of the 10 classes. We first generate one model for each class using an undersampled and oversampled datasets. Then for each of these models we created adversaries using its own current model and the balanced network. The balanced network itself was also tested using its own adversaries on all 10 classes at once to serve as baseline for our comparison. From now on we call this same model pertubation and different model pertubation, each being subdivided into the undersample and oversample case.

4 Results

The objective of this research is to understand the effects of adversarial attacks on imbalanced CNNs. However, it is firstly required to create the baseline for our comparisons. This consists of creating perturbation on every class label and querying its accuracy on a fully balanced model. Canonical models assume that every object in the dataset are sampled from similar distributions. However, in real-life situations, even though the number of samples is the same, some class labels could be poorly represented by the lack of a clear structure. This could often lead to differences in the output for each specific class [9]. On this way, a superficially balanced dataset does not guarantee that the model will equally generalise across all classes.

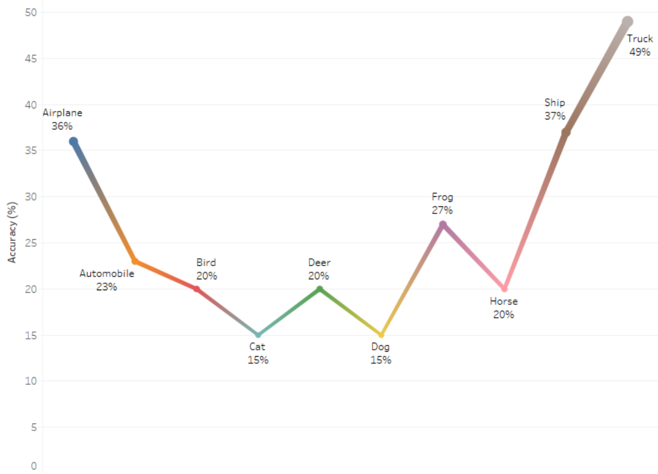


Fig. 2. Individual class perturbed accuracy on the balanced model

Figure 2 shows that the accuracy for all classes is drastically reduced when the balanced model is presented with adversarial examples. Even though there is enough samples for each class, the adversarial attack forces the domain shift of each individual sample towards different regions in space, causing a misclassification of the current label. The effectiveness of the adversarial attack can be partially explained by the balancing of the dataset itself. In a model where the dataset used in training aims for normalization over all classes, the network is often caught in trying to find weights and biases that generalizes well over all set of labels. Therefore, perturbations become more efficient due to a bigger proximity of classes distributions in space.

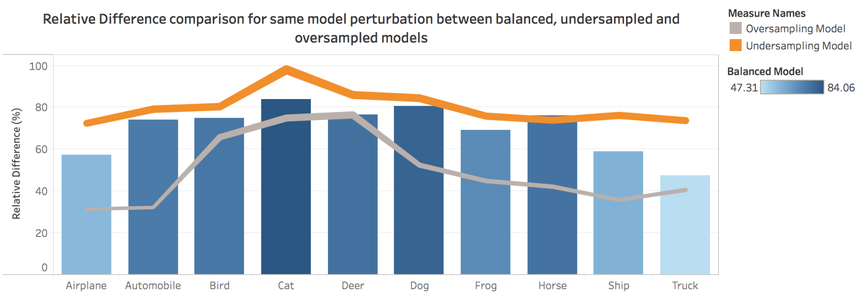
4.1 Class under-sampling and over-sampling

The adversarial test shows the results from two perspectives. First, on the class under-sampling with same model the accuracy for each individual class was on average 15%, which already demonstrates higher vulnerability when compared to the balanced case. This could be explained by having the data distribution of that specific class being squished into a smaller space and, hence, decreasing the amount of perturbation required to effectively increase the cost function so as to a misclassification to happen. Therefore, the degree of the perturbation required is reduced since the class label did not explore the feature space accordingly. Second, when oversampling occurs, it is expected to have the target class expanding into space and taking as much space as possible when compared to other classes. This happens since the network performs more gradient updates on that specific class due to the amount of available samples. Perturbation on this case had a lower effect, as the small push cause by our ϵ was not enough to move points to outside of their distributions.

	Different Model		Same Model		
Class Label	Undersample	Oversample	Balanced	Undersample	Oversample
0 - Airplane	60%	87%	36%	19%	61%
1 - Automobile	64%	91%	23%	16%	63%
2 - Bird	38%	73%	20%	9.4%	27%
3 - Cat	21%	72%	11%	0.5%	19%
4 - Deer	58%	80%	20%	9.8%	20%
5 - Dog	47%	76%	15%	9%	38%
6 - Frog	76%	88%	27%	20%	49%
7 - Horse	59%	88%	20%	18%	52%
8 - Ship	69%	89%	37%	19%	59%
9 - Truck	46%	87%	49%	21%	54%

Table 1. Results for the two different sources of perturbations along with the two different imbalanced datasets

As the number of samples on a target class goes down, an increase of vulnerability towards that specific label is expected when compared to the balanced model. The results on table 1 confirms this. Networks with imbalanced datasets were more vulnerable when presented with adversarial examples. Figure 3 shows the relative difference for all the three networks (balanced, under-sampled and oversampled). The values were calculated by finding the ratio between the new accuracy and the non-perturbed accuracy. They represent the percentage on which the initial accuracy was reduced. The under-sampled model had the higher relative difference on average, which shows that the imbalanced nature of the dataset ended-up increasing the vulnerability of the model. This poses threats to current systems as the low amount of samples during training for a specific class would create gaps that are more easily exploited when compared to a balanced network.



	Balanced Model	Oversampling Model	Undersampling Model
Airplane	57.14	31.46	72.46
Automobile	73.86	32.26	79.22
Bird	75.00	65.82	80.42
Cat	84.06	75.00	98.08
Deer	76.47	76.47	86.00
Dog	80.52	52.50	84.48
Frog	69.32	44.94	75.90
Horse	75.90	42.22	73.91
Ship	58.89	35.87	76.25
Truck	47.31	40.66	73.75

Fig. 3. Relative difference for each model. Higher numbers means more vulnerability

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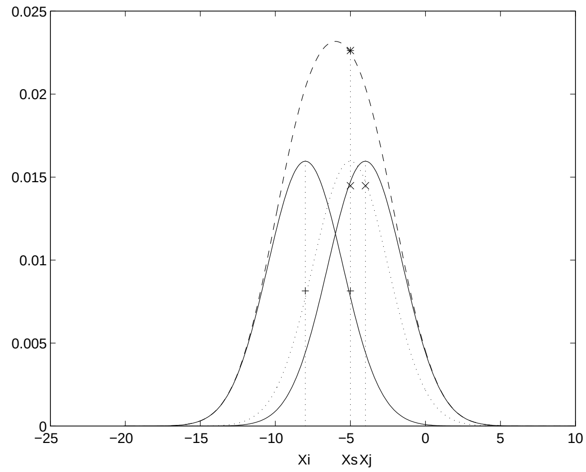

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$$\psi(u) = \int_o^T \left[\frac{1}{2} \left(\Lambda_o^{-1} u, u \right) + N^*(-u) \right] dt \; . \tag{3}$$

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```
program Inflation (Output)
  {Assuming annual inflation rates of 7%, 8%, and 10%,...
   years};
   const
```

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```
    MaxYears = 10;
  var
    Year: 0..MaxYears;
    Factor1, Factor2, Factor3: Real;
  begin
    Year := 0;
    Factor1 := 1.0; Factor2 := 1.0; Factor3 := 1.0;
    WriteLn('Year  7% 8% 10%'); WriteLn;
    repeat
      Year := Year + 1;
      Factor1 := Factor1 * 1.07;
      Factor2 := Factor2 * 1.08;
      Factor3 := Factor3 * 1.10;
      WriteLn(Year:5,Factor1:7:3,Factor2:7:3,Factor3:7:3)
    until Year = MaxYears
end.
```

(Example from Jensen K., Wirth N. (1991) Pascal user manual and report. Springer, New York)

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