Abstract. Recent analysis of deep neural networks has revealed their vulnerability to carefully structured adversarial examples. Many effective algorithms exist to craft these adversarial examples, but performant defenses seem to be far away. In this work, we attempt to combine denoising and robust optimization methods into a unified defense which we found to not only work extremely well, but also makes our model robust against future adversarial attacks. We explore the use of bilateral filtering as a projection back to the space of natural images. We first show that with carefully chosen parameters, bilateral filtering can remove more than 90% of adversarial examples from a variety of different attacks. We then adapt our recovery method as a trainable layer in a neural network. When trained under the adversarial training framework, we show that the resulting model is hard to fool with even the best attack methods.

1 Introduction

Deep neural networks have achieved outstanding performance in the fields of computer vision, text processing, and speech recognition. However, it has been shown that they are vulnerable to targeted perturbations added to benign inputs. The perturbed inputs, known as adversarial examples, can cause a classifier to output highly confident, but incorrect predictions. Adversarial examples are cheap to create, and defending against them is still an open problem.

The majority of prior work has studied adversarial examples in the context of computer vision, where adversarial examples pose the clearest threat. Small perturbations, imperceptible to humans, can be added to input images that cause a classifier to output false predictions. Because of the particular success of neural networks in computer vision, these networks are being deployed in areas like autonomous driving, facial recognition, and malware detection. Recent work has shown that these systems are vulnerable in the real world to adversarial examples [5], which makes the problem of resisting adversarial attacks a growing concern.

Many attacks and defenses have been proposed, and there has emerged two main methods for defending against adversarial examples. Denoising approaches attempt to remove the adversarial perturbations from the inputs as a preprocessing step. This is usually done by filtering, or by projecting the input to
a lower dimensional space that cannot represent high frequency perturbations \[26,28\]. These methods often perform very well, even on difficult datasets like ImageNet. But it has been shown that an attacker with knowledge of the defense can successfully circumvent them \[2\].

On the other hand, Adversarial training methods use an optimization approach to training robust models. Under the adversarial training framework, adversarial examples are combined with the natural training set to increase the model’s robustness to adversarial attack. These methods are expensive and have not been shown to scale well to large datasets like ImageNet.

## 2 Contributions

In this work we propose a method which combines denoising and adversarial training approaches, and yields a robust classifier which can defend well against adversarial examples. In particular, we study the application of the bilateral filter to the problem of recovering clean inputs from adversarial examples. Bilateral filtering is a classic and well-used approach in computer vision smooths only on areas without strong edges. We show that an edge-aware Gaussian filter such as the bilateral filter is able to reliably remove adversarial perturbations. We have found that, with appropriate parameters, bilateral filtering can recover 99% of the adversarial images so that a classifier can predict them correctly. We then introduce BFNet: an end-to-end model incorporating a differential bilateral filtering layer as a preprocessor. We show that BFNet is naturally robust to attacks from many first order adversaries, greatly reducing the strength of both $L_\infty$ and $L_2$ attacks. When combined with adversarial training, we achieve state of the art results on MNIST and CIFAR10. Our method works with zero knowledge of either the network or any incoming attack, making it applicable to a variety of models and datasets. Our contributions specifically are as follows:

1. We show that by using a bilateral filter, we can remove adversarial perturbations created by a variety of strong adversaries.

2. We develop an adaptive filtering network which predicts bilateral filter parameters from an input adversarial image. We test our network on the ImageNet dataset, using Inception V3 and InceptionResNet V2, and we found that our adaptive filtering network can reliably remove adversarial perturbations from natural images.

3. We show that BFNet is naturally robust to $L_2$ and $L_\infty$ bounded adversarial attacks on ImageNet. We also combine BFNet with adversarial training to further increase its resistance to attack. In particular, we evaluated the ability of adversaries to attack our network on the MNIST and CIFAR10 datasets, and achieve state of the art results on both for PGD and FGSM attacks.
3 Related Work

3.1 Adversarial Attacks

There have been many proposed attacks for creating adversarial examples. We give a brief description of the six attacks that we used to test our models.

A. Projected Gradient Descent (PGD)

When measuring the robustness of a model to adversarial attack, it is helpful to bound the strength of the adversary to generating perturbations of some allowed magnitude $\epsilon$. In [16,17], generating an adversarial example is the task of solving the objective:

$$\max_{\delta \leq \epsilon} L(\theta, x + \delta, y_{true})$$

PGD is used to minimize this objective, yielding an image with perturbations within the bounds of $\delta$, and achieves the highest possible loss.

B. Fast Gradient Sign Method (FGSM)

FGSM [9] is a one step linearization of the above objective. FGSM finds adversarial examples by assuming linearity at the decision boundary. Given an image $x$, we find a perturbation $\eta$ under the max norm:

$$\eta = \epsilon \cdot \text{sign}(\nabla_x L(\theta, x, y))$$

Where $\theta$ is the parameters of the network, $y$ is the original label, and $L$ is the cost function used to train the network.

C. Momentum Iterative Method

The Momentum Iterative Fast Sign Gradient Method (MI-FGSM) [6] is an iterative version of the FGSM attack, in that moves linearly toward the decision boundary. MI-FGSM improves on FGSM by introducing a momentum term into gradient calculation.

$$g_{t+1} = \mu \cdot g_t + \frac{\nabla_x L(x_t^*, y)}{\|\nabla_x L(x_t^*, y)\|_1}$$

The gradient is then used to iteratively update the image

$$x_{t+1}^* = x_t^* + \alpha \cdot (g_{t+1})$$

The authors claim that simply using an iterative FGSM leads to greedy overfitting of the decision boundary, and thus falls into local poor maxima. Adding momentum stabilizes the update direction and creates a stronger adversarial example.
D. L-BFGS-B

[29] used box-constrained L-BFGS to generate adversarial examples with minimal distortion under the $L_2$ norm. Given a natural image $x$ and a target class $y_{true}$, the adversarial objective is as follows

$$\min \left[ c \cdot \|x - (x + \delta)\|^2 + L(x + \delta, y_{target}) \right]$$

Where $\delta$ is the adversarial perturbation, $L$ is the loss function, and the parameter $c$ controls the trade-off between the magnitude and strength of the perturbation.

E. Carlini & Wagner Attack ($L_2$)

[3] proposed three iterative attacks which create adversarial examples under the $L_0$, $L_2$, and $L_\infty$ norms. In this work we consider the most powerful attack, the white-box $L_2$ attack. Specifically, they minimize

$$\min \| \frac{1}{2}(\tanh(w) + 1)x \|^2 + cf\left(\frac{1}{2}(\tanh(w) + 1)\right)$$

Where $f(x') = \max(\max\{Z_t(x') : i \neq t\}Z_t(x'), -\kappa)$

Here, $t$ is the target label, $Z$ refers to the logits of the network, $\kappa$ controls the confidence of the new classification, and the $\frac{1}{2}$ tanh term creates a box-constraint on the adversarial image of $[0, 1]$.

F. DeepFool

Deepfool is an iterative, first order method used to find minimal distortion under the $L_2$ norm [20]. Deepfool linearizes the classifier and performs gradient descent until the image is misclassified. The DeepFool objective is as follows:

$$\min_\delta \| \delta \|_2 \quad \text{subject to} \quad \text{argmax} f(x) \neq \text{argmax} f(x + \delta)$$

In addition to the attacks listed above, many other methods have been proposed. $L_0$ attacks such as [?] and

3.2 Adversarial Defenses

There is a growing body of work concerning defense against adversarial attacks [22][24][34][18][14]. Many of these lay an important foundation for our method. Removal of adversarial perturbations has been explored in many prior works, JPEG compression was studied in prior work [7][13][5]. JPEG compression was found to be an effective denoiser with respect to the. The authors note that predicting pixel values is not enough to clean an image, since remaining adversarial perturbations distort the model’s internal representation enough to cause a misclassification. To address this, they add a term to the loss function, which minimizes reconstruction error between the high level activations for natural and adversarial inputs. On the other hand, adversarial training methods [9][17][27][30] combine
adversarial examples with the natural training set to increase the model’s robustness to adversarial attack. These methods are promising as they attempt provide a guarantee on both the type of adversary and the magnitude of the perturbation they are resistant to. In practice however, these methods are hard to scale as they require expensive computation in the inner training loop to generate adversarial examples. When training on a large dataset like ImageNet, generating a sufficient amount of strong adversarial examples can be intractable. This problem has been mitigated by training against a weak adversary like FGSM \[30\] which can quickly generate adversarial examples. But training models that are robust to strong adversaries on ImageNet or Cifar10 is still an open problem.

4 Methods

Here we present our motivation for using a bilateral filter as the building block for our robust networks. We give a quick discussion of the theory of edge aware filtering and how it applies to adversarial examples. We show that it can remove adversarial perturbations crafted by many strong attacks. We then describe our end to end approach for training a classifier with a bilateral filter as a differentiable layer. Finally, we recognize the current state of the art method for training models robust to adversarial attacks, adversarial training, and we show that our method can extend adversarial training to create still more robust models.

Existing adversarial attacks fool deep networks by creating examples that do not come from the training distribution, and an effective defense would be to project the perturbed image back to a distribution similar to the training distribution. We observe that gradients in natural images are often piecewise-smooth; adversarial attacks perturb images such that the resulting gradients are locally nonsmooth with respect to the affected components of the image. An edge-aware Gaussian filter like the bilateral filter can be viewed as a projection back to the distribution of piecewise-smooth functions. The bilateral filter preserves local discontinuities (edges), while smoothing image gradients, for this reason the bilateral filter is a natural choice for removing adversarial perturbations.

By design, the perturbations in adversarial images have very small magnitudes, such that the perturbations are imperceptible to humans. In the case of multi-step attacks, the $L_\infty$ or $L_2$ bounded perturbation can be small enough that any blurring mechanism will simply average away the perturbation. Indeed it has been shown in prior work that JPEG compression \[7\] and foveation changes \[15\] are enough to remove perturbations from adversarial inputs. Both of these techniques represent changes to the input image that discard information that a human would not care about with regard to the task of classification. As stated before, the problem here is that a new optimization function can be created by an attack with knowledge of the defense. Because these methods did not demonstrate success against a direct attack, we cannot be sure of their performance against future attacks. On the other hand, bilateral filters can be formulated as a differentiable operation within a DNN and trained end to end. This new
network, which we call BFNet, can be validated against direct adversarial attack to test its robustness.

4.1 Threat Model

Prior work often presents adversarial attacks and defenses as being either a white-box or black-box. In the white-box threat model, the attacker has full access to training data, model parameters and architecture, and any other information else the attacker might need to mount a perfect-knowledge attack. The black-box threat model considers the case where the attacker has little to no knowledge about the model architecture, parameters, or training data. In the most restrictive setting, the attack may only have access to the argmax output of a softmax operation. In this work we consider white-box attacks, as they are categorically stronger adversaries than black-box attacks.

4.2 The Bilateral Filter

The bilateral filter is a non-linear Gaussian filter that is used to smooth an image while preserving sharp edges. Similar to other Gaussian filters, the bilateral filter replaces pixel values with a weighted average of the neighboring intensity values. Edges are preserved because the weighting is done according to both pixel-wise Euclidean distance as well as differences in range, intensity, depth, etc. For an image $I$, window $\Omega$ centered at coordinate $x$, the bilateral filter is formulated as follows:

$$I_{\text{filtered}}(x) = \frac{1}{W_p} \sum_{x_i \in \Omega} I(x_i)f_r(||I(x_i) - I(x)||)g_s(||x_i - x||)$$

Where the normalization term is $W_p = \sum_{x_i \in \Omega} f_r(||I(x_i) - I(x)||)g_s(||x_i - x||)$.

Fig. 1: The effect of filtering on a L-BFGS-B adversarial image. (a) is the original adversarial image, (b) is the image after 3x3 bilateral filtering and (c) is the image after 3x3 average pooling. The bilateral filter is superior when removing small perturbations while preserving the underlying class features.
To test the efficacy of the bilateral filter to recover clean inputs from adversarial examples, we generated a set of adversarial examples from a range of powerful adversaries. Our first naive approach was to manually tune parameters for each input image, to test the effective range of parameters which could denoise an adversarial example. We found that with carefully chosen parameters, most of the images we generated could be recovered. Our experiments showed that the small perturbations created by iterative methods like the Carlini & Wagner attack, and DeepFool were easier to remove with a bilateral filter, than the larger perturbations created with one step attacks. We were able to remove perturbations from iterative attacks by using small filters 3 - 5 pixels wide, and $\sigma_s, \sigma_c$ values of less than 1. One step attacks perturb every pixel in the image with the same magnitude of noise. As a result, we used a larger filter and $\sigma_s$ to remove the perturbations.

Note that we can parameterize the bilateral filter in terms of the size of the filter $\Omega$, and the strength of the two Gaussian functions $\sigma_s$ and $\sigma_r$. This makes it possible to train a classifier to predict what parameters will be needed to filter an image, while preserving the features underlying the noise.

Fig. 2: The effect of bilateral filtering on adversarial inputs. From left to right, we show the clean image, the adversarial images generated by the respective attack algorithms on the Inception v3 network, and the recovered image after bilateral filtering. After filtering, the input images can safely and correctly classified.
4.3 Adaptive Filtering

One caveat to this method, is that the parameters for the bilateral filter must be carefully chosen such that the accuracy and confidence of the classifier are preserved. Large \( \sigma_s \) and \( \sigma_r \) values can create an excessively blurred image, and a small filter size may fail to remove the adversarial perturbations. With this in mind, we train a small network which will predict the parameters of the bilateral filter for a given image. This network will serve as a cheap preprocessing step that will remove adversarial perturbations without affecting the underlying class label. In table 1 we see that the adaptive filtering approach can remove over 80\% of adversarial perturbations from ImageNet images, crafted by strong first order methods. In addition, we found that we were successful in defeating the attack itself in over 95\% of the test images. If the original class label cannot be recovered with certainty, than it is important that the any malicious attack not proceed unarrested. Our adaptive filtering approach ensures that an adversary is either completely defeated, or stopped from mounting targeted attacks.

4.4 Robust Denoising Network

It has been shown that under the white-box threat model, using a denoiser as the only defense is insufficient to stop the strongest adversarial attacks. A preprocessing stage works best with transferred adversarial examples, that is, adversarial examples generated against a different classifier with no knowledge of the defense. Currently the most promising direction for training models robust to adversarial attacks is adversarial training. Despite continuing progress on both MNIST and CIFAR10, adversarial training is still very expensive, and performs worse than denoising approaches on the same datasets. We propose a combining adversarial training with our denoising approach, giving a robust, performant classifier in the context of our threat model.

Following [1,2,3], the adversarial training framework can be expressed as the saddle point problem:

\[
\min_{\theta} f(x; \theta) \quad \text{where} \quad f(x; \theta) = \mathbb{E}_{(x,y) \sim D} \left[ \max_{\delta} L(\theta, x + \delta, y_{true}) \right]
\]

Where a solution to the inner maximization problem represents the most adversarial example within some perturbation budget. Solving the outer minimization problem yields a classifier which is robust to the above adversary. [1] showed that PGD could reliably solve the inner maximization problem without linearizing it, and is thus a better adversary to train against than FGSM.

We propose a modification to the above saddle point formulation which incorporates a powerful preprocessing function \( p(x) \). This precludes the use of non-differentiable defenses like JPEG compression in this saddle point formulation. We choose as our preprocessing function the Permutohedral Lattice implementation of the bilateral filter [2], which is fully differentiable and can be computed in linear time with respect to the number of pixels in the image. This gives us
the following objective:

$$\min_{\theta} f(p(x)) \quad \text{where} \quad f(x) = \mathbb{E}_{(x,y) \sim D} \left[ \max_{\delta} L(\theta, x + \delta, y_{\text{true}}) \right]$$

$$p(x) = \frac{1}{W_p} \sum_{x_i \in \Omega} I(x_i)f_r(||I(x_i) - I(x)||)g_s(||x_i - x||)$$

Here $p(x)$ is the bilateral filter, represented as convolutions of an image $x$ with two Gaussian filters. From this point on we will simply refer to $p(x)$ as BF$_{\text{diff}}$. To train our model we use the same experimental setup as in [1]. We train our model using the adversarial framework against FGSM and PGD adversaries, and evaluate on MNIST and CIFAR10.

For MNIST we construct a model with the same architecture as [3], and prepend our BF$_{\text{diff}}$ layer to the first convolutional layer. We observe a faster decrease in training loss, and increased robustness to white-box FGSM, PGD, and CW attacks. In addition, we train against a FGSM adversary and show that we do similarly well against further attack. To test our model against Cifar10, we train a small 5 layer convolutional network, as well as ResNet18. We add our BF$_{\text{diff}}$ layer to the input of our networks and train them end to end. For both experiments we train against 20 step PGD as an adversary, and we show that our BFNet is more robust than a standard adversarially trained model.

Because adversarial examples pose a real world risk to mission-critical AI systems, we plan to open-source our models and implementation soon. We believe it is especially important for defenses against adversarial defenses to be open and validated.

5 Experiments

5.1 Adaptive Filtering Model

In this section we show that our model can correctly predict filtering parameters which will denoise an adversarial input. To test this, we generate a dataset of 1000 adversarial images with five different attacks: Projected Gradient Descent with 40 steps (PGD), Box constrained L-BFGS, The Carlini & Wagner $L_2$ attack (CW), The Momentum Iterative FGSM (MIM), FGSM, and Deepfool

Where applicable, we constrain the perturbations to an epsilon ball of radius 0.3 from the training example. Source images have been normalized to a range of $[-1, 1]$

Network Architecture To build our classifier we first extract information about the distribution of pixel gradients by convolving the input with a Sobel filter in the $x$ and $y$ direction. Because adversarial attacks directly change values of the input, adversarial examples will often have larger color gradients in the $x$ and $y$ direction than natural images. We concatenate the gradient map with
Table 1: Recovery performance for manually chosen bilateral filter parameters. We measure recovery by the percentage of examples which, after filtering, revert to the classification label assigned to the same, unperturbed image. We use odd filter diameters of size 3, 5, 7 and $\sigma_s$, $\sigma_r$ are chosen from the set 0.5, 1, 3. This shows that with carefully chosen parameters, we can recover nearly all adversarial examples.

| Network             | FGSM | ML-FGSM | DeepFool | CW ($L_2$) | L-BFGS |
|---------------------|------|---------|----------|------------|--------|
| Inception V3        | 97.0 | 97.5    | 98.8     | 99.2       | 97.8   |
| InceptionResNet V2  | 94.2 | 98.4    | 96.3     | 98.8       | 95.1   |
| ResNet V2           | 96.5 | 98.0    | 96.1     | 98.1       | 98.0   |

the input, and use three dilated convolutional layers with 64, 128, and 256 filters respectively, followed by 2x2 max pooling and a linear layer of 64 units. We use a dilation rate of 2 for each of the convolutional layers.

To construct our training set we use 1000 images generated from each of the attacks in table 1. For each image, we collect labels in the form of triples $(k, \sigma_r, \sigma_s)$, $k$ denotes the kernel size, and $\sigma_r$, $\sigma_s$ are the standard deviation for the domain and range functions respectively. Given any adversarial example, there may be many permutations of parameters for the bilateral filter that successfully denoise the input. For this reason we collect a maximum of 10 different parameter configurations for each image in our training set. Given this is a multi-class prediction problem, we train using a sigmoid function at the output to predict all candidate parameter configurations. At test time we evaluate with the parameters predicted by the maximally activated output unit. Our results are presented in tables 2 and 3.

We used the pretrained Inception V3 [2] and InceptionResNet V2 [1] ImageNet classifiers as our source networks. To generate adversarial examples on these networks, we used the open-source Cleverhans toolbox [23]. the model was trained using SGD with Nesterov momentum for 25 epochs. We then test on six different validation sets, one for each adversary respectively.

It can be seen that we can recover adversarial examples generated by FGSM, PGD, CW and DeepFool near perfectly, while missing nearly 15% of the examples of MIM and L-BFGS. These results are significantly better than the results in [14], which used a 3x3 average filter to recover images. Our Adaptive Filtering network succeeds in removing adversarial examples generated on natural images, and it does so using a relatively simple method. This makes the Adaptive Filtering network a viable method for quickly cleaning data without needing to train and run more complicated denoising models.
Table 2: Performance of our adaptive bilateral filter (AF) across different attacks. We show the success rate of the top5 parameter predictions with respect to recovering the original classification label from the adversarial example (A). We also show how often AF is able to default the adversarial attack, that is, change the classification from the adversarial label to a new one. InceptionResNet V2 is known to be a more robust network than Inception V3, The adversarial examples that succeed in fooling it are comparatively more robust.

| Source Network          | Clean | FGSM | PGD | MIM | CW | DeepFool | L-BFGS |
|-------------------------|-------|------|-----|-----|----|----------|--------|
| Inception V3ₐ           | 95.0  | 89.0 | 90.7| 79.1| 89.1| 90.3     | 81.3   |
| InceptionResNet V2ₐ     | 91.1  | 87.2 | 87.1| 75.3| 87.8| 85.0     | 80.8   |
| Inception V3ₜ           | 95.0  | 95.9 | 98.0| 96.4| 94.1| 95.3     | 96.2   |
| InceptionResNet V2ₜ     | 91.1  | 93.1 | 98.0| 94.3| 97.8| 92.0     | 95.3   |

Table 3: Classification accuracy of ImageNet classifiers when our adaptive filtering network is used as a preprocessing stage before classification. We report both top1 and top5 classification accuracy for Inception V3 (Inc V3) and InceptionResNet V2 (IncResNet V2).

| Network                  | Clean | FGSM | PGD | MIM | CW | DeepFool | L-BFGS |
|-------------------------|-------|------|-----|-----|----|----------|--------|
| AF + Inc V3 top1        | 71.7  | 71.0 | 71.6| 63.1| 71.1| 70.1     | 64.2   |
| AF + Inc V3 top5        | 89.6  | 84.0 | 86.3| 74.6| 84.1| 85.2     | 76.7   |
| AF + IncResNet V2 top1  | 73.1  | 70.1 | 70.8| 60.5| 70.3| 70.5     | 65.0   |
| AF + IncResNet V2 top5  | 86.7  | 83.1 | 82.8| 71.7| 83.6| 85.6     | 77.0   |

5.2 Robust Denoising Network

**MNIST** To show that our model is robust to strong first-order adversaries, we train a small convolutional network to 99.2% accuracy on the test set. Our vanilla model consists of 2 convolutional layers with 32 and 64 filters respectively, each followed by 2 x 2 max pooling and ReLU. We use a final fully connected layer with 1024 units. As with the ImageNet experiments, we modify our network into a BFNet by adding our bilateral filter layer at the input of the network. We then adversarially train our BFNet using three distinct adversaries: FGSM, PGD, and PGD with the CW loss function. We report the results in table 4. Our results outperform the state-of-the-art adversarial training results. We also
show that while our network is only trained on one adversary, we are robust to attacks from other adversaries.

Table 4: Comparison of our method with state of the art adversarial training results. BFNet$_{pgd}$ denotes our model trained against a PGD adversary, while BFNet$_{fgsm}$ is trained against a FGSM adversary. For Tramer et al. We report A: the strongest white box attack given against a non-ensembled model from [30], as well as B: the performance of architecture B from [17].

| Network       | Clean | FGSM | PGD  | CW  | CW ($\kappa = 50$) |
|---------------|-------|------|------|-----|---------------------|
| BFNet$_{pgd}$ | 99.0  | 95.5 | 98.0 | 93.2| -.-                 |
| Madry et al   | 98.8  | 95.6 | 93.2 | 94.0| 93.9                |
| BFNet$_{fgsm}$| 99.0  | 98.1 | 36.4 | 88.2| 96.0                |
| Tramer et al A| 98.8  | 95.4 | 96.4 | -.- | 95.7                |
| Tramer et al B| 98.8  | 97.8 | -.-  | -.- | -.-                 |

We can see the resulting model is very robust, indeed that images that fool either the BFNet$_{fgsm}$ or BFNet$_{pgd}$ are so different that they appear adversarial to a human as well.

Fig. 3: Successful PGD adversarial examples generated against an adversarially trained BF$_{PGD}$ with $\epsilon = 0.3$
Fig. 4: Successful FGSM adversarial examples generated against an adversarially trained BF\textsubscript{fgsm} with $\epsilon = 0.3$

CIFAR10 We perform similar experiments for CIFAR10. Primarily we use a network with four convolutional layers, each followed by 2x2 max pooling. We use a wide linear layer of 4096 units before softmax. As with our MNIST experiments, we add a BF\textsubscript{diff} layer to the beginning of the network. When naturally trained with Adam for 30 epochs, this network reaches an accuracy of 79.04% on the test set. We also train the original ResNet model used in [17] for 80K iterations. Trained on natural samples we reach an accuracy of 92.7% on the test set. Each model is trained adversarially with PGD and FGSM. We use an $L_\infty$ bound of $\epsilon = 8$ for both adversaries. For PGD we take 20 steps with a learning rate of 2.0. We report our results in table 5

| Method       | Network | Clean | FGSM | PGD  |
|--------------|---------|-------|------|------|
| BFNet\textsubscript{pgd} | A.      | 87.1  | 55.2 | 50.4 |
| BFNet\textsubscript{pgd} | B.      | 73.1  | 64.5 | 38.1 |
| BFNet\textsubscript{fgsm} | B.      | 76.5  | 70.6 | 12.2 |
| Madry et al  | C.      | 87.3  | 56.1 | 45.6 |

5.3 ImageNet

Due to the high cost of adversarial training on natural images, we test robustness of ImageNet classifiers when they are modified only with a bilateral filter layer at
the input. We use the Inception V3 and the Inception-ResNet V2 networks, and add our bilateral filtering layer to the input, keeping the pretrained ImageNet weights. We test against both $L_2$ and $L_\infty$ adversaries to obtain a complete picture of adversarial robustness. $L_\infty$ is a more reasonable metric when discussing the magnitude of adversarial attacks on very small images, because a large perturbation measured under the $L_\infty$ norm equates to a large visual change. But with larger, natural images, a perturbation with a large $L_\infty$ distance is less interpretable. A large change to a single pixel may still go unnoticed to a human observer, while a large perturbation under the $L_2$ norm gives more information about the total distortion caused by the adversarial attack.

5.4 $L_2$ Robustness

To measure resistance to attacks under the $L_2$ norm, we use the unbounded attacks L-BFGS and DeepFool. It is impossible to be fully resistant to unbounded attacks, because any image can be changed to a completely different image as long as there is no bound on the size of the perturbation. In this case, we report the average $L_2$ and $L_\infty$ distance of the generated adversarial images from the unbounded attacks.

We can see that our approach yields a very robust model against adversarial perturbations under the $L_2$ metric. When attacking our BFNet models with DeepFool, we see that the generated adversarial image has an $L_\infty$ distance over 30x larger, when compared to an unmodified network of the same architecture. Similarly, we can see that the $L_2$ distance of an adversarial generated against BFNet is far larger when compared to adversarial images generated against a network of the same architecture without the bilateral filter. With respect to the L-BFGS attack, we see a similarly large disparity between BFNet and a vanilla network.

Table 6: Performance of BFNet against the unbounded DeepFool attack. We report the average $L_2$ and $L_\infty$ distance of 1000 adversarial images on Inception V3 and Inception-ResNet V2.

| Network              | $L_\infty$ | $L_2$  |
|----------------------|------------|--------|
| Inception V3$_{\text{Natural}}$ | 0.015      | 0.43   |
| Inception V3$_{\text{BFNet}}$    | 0.621      | 148.29 |
| IncResNet V2$_{\text{Natural}}$  | 0.025      | 0.44   |
| IncResNet V2$_{\text{BFNet}}$    | 0.793      | 187.45 |
Fig. 5: Comparison of adversarial images created with BFNet vs a vanilla unmodified classifier

(a) Adversarial images generated with DeepFool on a vanilla Inception V3 classifier. The adversarial images are visually identical to the real images, and have an average $L_2$ norm of 0.09.

(b) Adversarial examples generated by an L-BFGS adversary on a vanilla Inception V3 classifier. The adversarial examples have an average $L_2$ distance of 0.025 from their natural counterparts, and have visually imperceptible perturbations.

(c) Adversarial examples generated by L-BFGS on a BFNet version of the Inception V3 classifier. Generated adversarial examples have visually identifiable perturbations, and have an average $L_2$ norm of 106.2.

(d) Adversarial examples generated by DeepFool on a BFNet version of the Inception V3 classifier. The generated adversarial examples have large, noisy perturbations, and have an average $L_2$ norm of 181.2.
Table 7: Performance of BFNet against unbounded L-BFGS attack. We report the average $L_2$ and $L_\infty$ distance of 1000 adversarial images on Inception V3 and Inception-ResNet V2.

| Network          | $L_\infty$ | $L_2$  |
|------------------|------------|--------|
| Inception V3Natural | 0.02      | 0.67   |
| Inception V3BFNet    | 0.39      | 90.52  |
| IncResNet V2Natural  | 0.06      | 0.77   |
| IncResNet V2BFNet    | 0.65      | 90.65  |

5.5 $L_\infty$ Robustness

For the $L_\infty$ attacks such as FGSM, and MI-FGSM we measure the resistance of our model to different values of perturbation $\epsilon$. We can see that our BFNet significantly decreases the attack strength of $L_\infty$ adversaries, in most cases by over 50%. Of particular note is that we show more significant resistance to adversarial perturbations of $\epsilon \leq 0.3$. Larger perturbations are visually discernible, and thus are less adversarial than smaller fooling perturbations. For both attacks we use 1000 random images sampled from the ILSVRC 2012 validation set, and report the percentage of successful attacks against both the natural model, and the BFNet modified network for a wide range of epsilon values.

Table 8: Performance of BFNet against an FGSM adversary for a range of perturbation sizes (lower is better)

| Network          | Epsilon | Natural | BFNet |
|------------------|---------|---------|-------|
| Inception V3     | 0.1     | 73.2    | 30.2  |
| Inception V3     | 0.15    | 78.6    | 36.6  |
| Inception V3     | 0.3     | 93.2    | 46.6  |
| Inception V3     | 0.5     | 99.0    | 63.2  |
| Inception V3     | 0.75    | 100.0   | 90.8  |
| Inception V3     | 1.0     | 100.0   | 99.8  |
| IncResNet V2     | 0.1     | 58.8    | 42.6  |
| IncResNet V2     | 0.15    | 65.6    | 55.4  |
| IncResNet V2     | 0.3     | 88.2    | 75.4  |
| IncResNet V2     | 0.5     | 98.0    | 91.0  |
| IncResNet V2     | 0.75    | 99.6    | 99.6  |
| IncResNet V2     | 1.0     | 99.6    | 99.6  |
Table 9: Performance of the BFNet against an MI-FGSM adversary. We again report the performance of BFNet against an unmodified network for a variety of values of epsilon. For our MI-FGSM attack, we use a momentum decay factor of 1.0, and run the attack for 10 iterations.

| Network      | Epsilon | Natural | BFNet |
|--------------|---------|---------|-------|
| Inception V3 | 0.1     | 58.8    | 21.0  |
| Inception V3 | 0.15    | 65.6    | 30.1  |
| Inception V3 | 0.3     | 88.2    | 42.2  |
| Inception V3 | 0.5     | 98.0    | 52.4  |
| Inception V3 | 0.75    | 99.6    | 53.4  |
| Inception V3 | 1.0     | 99.6    | 70.8  |
| IncResNet V2 | 0.1     | 89.1    | 59.0  |
| IncResNet V2 | 0.15    | 90.6    | 38.6  |
| IncResNet V2 | 0.3     | 92.2    | 59.4  |
| IncResNet V2 | 0.5     | 100.0   | 74.6  |
| IncResNet V2 | 0.75    | 100.0   | 80.2  |
| IncResNet V2 | 1.0     | 100.0   | 91.8  |

Conclusion

The continued existence of adversarial examples, and the lack of effective defenses limits our ability to deploy AI systems in critical areas where safety and security are necessary. It is still an open problem to create optimization techniques that cannot be subverted, or networks that cannot be fooled. Here we present a simple yet novel approach to recovering clean inputs from adversarial examples, and show how it can extend adversarial training to create a robust model to strong adversarial attacks.

We showed that a bilateral filter can be used as a versatile, effective preprocessor to clean images before classification. The bilateral filter remains effective when deployed with numerous defense strategies: as a manual preprocessing step, a trained denoiser, or a robust model that’s trained end-to-end. Because the bilateral filter encourages piecewise smoothness, we see that the bilateral filter effectively projects adversarial images back to the distribution of natural images. Furthermore, when trained end to end, our bilateral filter can be combined with adversarial training approaches to create a robust defense method. In the future we hope to see preprocessor defenses tested by direct white-box attack, and combined with robust optimization methods like adversarial training to create performant, unified defenses.
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