On the Benefits of Attributional Robustness

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Abstract

Interpretability is an emerging area of research in trustworthy machine learning. Safe deployment of machine learning system mandates that the prediction and its explanation be reliable and robust. Recently, it was shown that one could craft perturbations that produce perceptually indistinguishable inputs having the same prediction, yet very different interpretations. We tackle the problem of attributional robustness (i.e. models having robust explanations) by maximizing the alignment between the input image and its saliency map using soft-margin triplet loss. We propose a robust attribution training methodology that beats the state-of-the-art attributional robustness measure by a margin of \( \approx 6\%-18\% \) on several standard datasets, ie. SVHN, CIFAR-10 and GTSRB. We further show the utility of the proposed robust model in the domain of weakly supervised object localization and segmentation. Our proposed robust model also achieves a new state-of-the-art object localization accuracy on the CUB-200 dataset.

1. Introduction

Application of machine learning algorithms in various safety-critical domains is being hindered due to the blackbox nature of these techniques. Robustness and interpretability of machine learning methods has become a crucial topic and a pre-requisite for successful deployment in various fields (e.g. self-driving cars, medical diagnosis). Hence, the field of explanation is attracting a lot of attention as it offers insight into decision making procedure of machine learning techniques. Attribution/saliency methods are an increasingly popular class of explanation techniques that aim to highlight relevant input features responsible for prediction.

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Figure 1: Illustration of an attributional attack [18]; Top row: original image and its attribution map; Bottom row: perturbed image and its attribution map [59]

Most deep learning research in the area of robustness is focused around the robustness to adversarial perturbations [24, 60]. Adversarial perturbations are imperceptible perturbation when added to input drastically change the neural network’s prediction. In contrast, in this paper, we focus on another type of robustness measure for neural networks which we refer to as attributional robustness. Recently, [23, 18] demonstrated that one can generate minimal perturbations that can substantially change the model’s interpretations, while keeping the predictions intact. Unfortunately, while the area of adversarial robustness is well studied, there has only been limited progress made on the front of attributional robustness.

We show in figure 1 the vulnerability of image classifiers to attribution based attacks. The intuition of attributional robustness is that if the prediction and input of model remains intact, then so should the interpretation. It has been demonstrated that one can construct targeted [18] and un-targeted attributional perturbations [23, 14] that can manipulate the
amount of changes induced in the attribution maps without affecting the model’s prediction. This is a particularly alarming issue as it further weakens the cause of safe application of machine learning algorithms to real-world tasks.

The authors of [14] propose a training methodology that aims to obtain models having robust integrated gradient [59] attributions. However, sometimes the instability of this training methodology as discussed in [14] limits its usability in the boarder context of robust attribution in computer vision. In this paper, we introduce a training technique that achieves state-of-the-art attributional robustness across different attribution methods [53, 59] and also show its utility in the domain of weakly supervised object detection and segmentation.

Specifically, we introduce an attribution training methodology that uses soft-margin triplet loss to promote the alignment of an input with its attribution map. The triplet loss considers the input image as the anchor, the gradient of the correct class logit with respect to input as the positive and the gradient of the worst incorrect class logit with respect to input as the negative. The intuition behind this loss choice is that the gradient of the correct class logit with respect to input should have the highest similarity with input as compared to gradient of any other class logit with respect to input. We show empirically how this choice results in attributional robustness of neural network and helps in other weakly supervised tasks.

To summarize our main contributions are:

- We introduce the concept of attributional robustness and highlight the significance of it as a general measure that helps broaden the notion of robustness for neural networks.
- We propose a robust attribution training methodology that aims to maximize the alignment between the input and its attribution map [53]. The proposed model training technique achieves state-of-the-art attributional robustness on various saliency methods.
- We empirically show that the proposed training methodology also induces significant immunity to adversarial perturbations and common perturbations on standard vision datasets.
- We demonstrate the utility of our proposed attributional training approach for other computer vision tasks such as weakly supervised object localization and segmentation. Specifically, our proposed model achieves the new state-of-the-art result in weakly supervised object localization on CUB dataset using attributional robustness.

2. Related Work

Our work is associated with various recent developments made in the field of reliable explanation methods, weakly supervised object localization and robustness to input distribution shifts.

Visual Explanation Methods Various explanation methods have been proposed that focus on producing posterior explanations for the model’s decisions. A popular approach to do so is to attribute the predictions to the set of input features [53, 57, 52, 59, 51, 8] that can be referred to as attribution or saliency methods. Sample-based explanation methods [32, 70] leverage previously seen examples to describe the prediction of the model. Concept-based explanation techniques [9, 31] aim to explain the decision of the model by high-level concepts. Additionally, there has been some work that explores interpretability as a built-in property of architecture inspired by the characteristics of linear models [6], [78, 19] provide a survey of interpretation techniques. In this paper, we will be focusing on attribution-based methods that generate visual, image-like explanations. Attribution methods can be broadly divided into three categories - gradient/back-propagation, activation and perturbation-based methods.

Gradient-based methods attribute an importance score for each pixel by calculating derivative of a class score with respect to input image pixels [53, 52]. Further improvements have been proposed in which gradients are accumulated along a path from a reference image to input image [59], or by only considering the gradients through positive activation while back-propagating [73, 57] or by aggregating gradients on multiple noisy images of the original image to obtain attribution maps [56, 1]. Techniques in [8, 51, 76] leverage layer-wise propagation computation to calculate the attribution maps. Activation-based explanation techniques generate the attribution maps by using a weighted linear combination of the convolutional’s activation. [82, 50, 13]. Perturbation-based interpretation methods generate attribution maps by examining the change in prediction of the model when the input image is perturbed [73, 46, 48]. Related to this, similar methods [17, 22, 66, 12] generate an explanation by optimizing for a perturbed version of the image.

Robustness of Attribution Maps Recently, several research work [79, 23, 18, 14, 5] has been exploring the robustness of attribution maps, that we refer to as attributional robustness. The authors of [23, 18, 79] study the robustness of a network’s attribution maps and show that these saliency maps can be significantly manipulated via imperceptible input perturbations while preserving the classifier’s prediction. [14] proposes a robust attribution training methodology.
Adversarial Perturbation Adversarial attacks can be broadly categorized into two types: White-box [39, 37, 11, 69] and Black-box attacks [28, 63, 4, 45]. White-box attack assumes full access to the network while in the latter, information about the network is not available. Defense strategies to improve the adversarial robustness of deep networks include the use of regularizers inspired by reducing the Lipschitz constant of the neural network [62, 16]. However, many of proposed defense techniques were shown to be ineffective to adaptive adversarial attacks [7, 35, 11, 10]. Hence, we focus on adversarial training which [25, 37, 55] is a defense technique that continuously augments the data with adversarial examples while training. Techniques relying on adversarial training constitutes the current state-of-the-art in adversarial robustness. The authors of [75] characterize the trade-off between accuracy and robustness for classification problems and propose a regularized adversarial training method. Recent work of [47] proposes a regularizer that encourages the loss to behave linearly in the vicinity of the training data and [74] improves the adversarial training by also minimizing the convolutional feature distance between the perturbed and clean examples. Prior works have also attempted to improve the adversarial robustness using gradient regularization which minimizes the Frobenius norm of the Hessian of the classification loss with respect to input [49, 40, 36] or weights [29]. In the context of this paper we will mainly focus on perturbations of \( \| \nabla f \|_p \) norm bound rather than other constraint bounds [68, 20]. For a comprehensive review of the work done in the area of adversarial examples, please refer [71, 3].

Weakly Supervised Object Localization (WSOL) The problem of WSOL aims to identify the location of the object in a scene using only the image-level labels, and without any location annotations. Generally, rich labeled data is scarcely available and it’s collection is expensive and time consuming. Therefore, the field of learning from weak supervision is quite promising as it requires less rich labels and thus has the potential to scale. A common problem with most of the previous approaches is that the model only identifies the most discriminative part of the object rather than the complete object. For example, in the case of a bird, the model may rely on the beak region for classification than the entire bird’s shape. In WSOL task, ADL [15] is the current state-of-the-art method that uses an attention based dropout layer while training the model that promotes the classification model to also focus on less discriminative parts of the image. For getting the bounding box from the model, ADL and similar other techniques in this domain first extract attribution map, generally CAM[82], for each image and then fit a bounding box on this as presented in [82].

3. Methodology

We consider a neural network \( f_{\theta} : \mathbb{R}^n \rightarrow \mathbb{R}^k \) with relu activation functions which classifies an input image \( x \in [0,1]^n \) into \( k \) classes with true label \( y \in \{1...k\} \). The logit value corresponding to class \( i \in \{1...k\} \) is denoted as \( f(x)_i \). For a given class \( i \), attribution map is referred as \( I(x,f_i) \) that assigns an importance score to each input pixel of \( x \) based on its relevance for predicting the class \( i \).

3.1. Attributional Robustness

We define a classification model \( f_{\theta} \) to be attributionally robust if the attribution maps do not change drastically with slight perturbation to inputs. The objective of attributional robustness is to ensure that similar feature importance is assigned to pixels for visually similar images.

Attributional Attack Attributional robustness measures the maximum possible change in attribution map on applying a small norm bounded perturbation \( \delta \) to \( x \) over the dataset. The problem of calculating \( \delta \) can be formulated as

\[
\arg \max_{\delta \in B_\epsilon} D[I(x + \delta, f(x + \delta)_y), I(x, f(x)_y)] \\
\text{subject to: } \arg \max(f(x)) = y
\]

where \( B_\epsilon \) is an \( \epsilon \) ball under \( p \) norm which bounds the norm of \( \delta \) with which input \( x \) can be perturbed and \( D \) measures distance/dissimilarity between two attribution maps. After obtaining \( \delta \), we calculate similarity (e.g. using spearman correlatin [23], kendall’s tau coefficient [14]) between attribution map of original image \( x \), and perturbed image \( x + \delta \), to get a measure of attributional robustness in the \( \epsilon \) neighbourhood of sample \( x \). Taking an expectation over the validation set of data gives us an approximate empirical measure of the attributional robustness of the network for a particular dataset. Some examples of dissimilarity measures for calculating \( \delta \) have been proposed in [18, 23]. In the next section, we propose the formulation for our attributional robust training methodology.
3.2. Saliency Robustness Training

In our training methodology, given an input image \( x \in \mathbb{R}^n \) and its label \( y \), we calculate its attribution map with respect to output logit \( i \in \{1...k\} \) via \( \nabla_x f(x) \). We will use \( g_i(x) \) to denote \( \nabla_x f(x)_i \) in our paper. Our aim is to make \( g_y(x) \) and classification loss landscape invariant in the local neighbourhood of \( x \) by optimizing the following objective:

\[
\min_{\theta} \mathbb{E}_{(x,y)} \left[ L_{ce}(x+\delta,y) + \max_{\delta \in B_x} L_{attr}(g_y(x+\delta)) \right]
\]

where \( L_{ce} \) is the standard cross entropy loss and \( L_{attr} \) is the loss that encourages the alignment of \( g_y(x) \) with \( x \). Here, \( L_{attr} \) promotes similar images to possess similar attribution maps. We take motivation from the fact that meaningful saliency maps of images are perceptually similar to image itself. We define \( L_{attr} \) as:

\[
L_{attr}(x) = \log(1 + \exp(-(d_{neg} - d_{pos})))
\]

where \( d_{pos} = 1 - \cos(g_y(x), x) \)
\( d_{neg} = 1 - \cos(g_j(x), x) \)
\( j^* = \arg \max f(x) \)

\( L_{attr} \) is a soft-margin triplet loss with anchor \( x \), its positive instance \( g_y(x) \) and its negative instance \( g_j(x) \). The idea being that attribution map calculation with respect to different class logit value should be different and \( g_y(x) \) should have the largest perceptual similarity with the image \( x \).

Thus, our final training methodology consists of two steps: first, we calculate a perturbed image \( \tilde{x} = x + \delta \) that maximizes \( L_{attr} \) by using iterative projected gradient descent; secondly, we use \( \tilde{x} \) as the new training point on which \( L_{ce} \) and \( L_{attr} \) is minimized. We point out that this min-max formulation is different from adversarial training \([37]\), as only \( L_{attr} \) is maximized to calculate the perturbation \( \delta \). Figure 2 shows the block diagram of our training approach.

![Figure 2: Block diagram summarizing our training technique for attributional robustness. Here, C.E. denotes cross entropy loss, dashed line represents the backward gradient flow and the bold lines denotes forward call in neural network.](image)

**Algorithm 1** Proposed training for attributional robustness

begin

Input: Training Data \( X = \{(x_1,y_1)\ldots(x_N,y_N)\} \), batch size \( b \), number of epochs \( E \), learning rate \( lr \), number of attack steps \( a \), step-size for iterative perturbation \( \alpha \)

Output: \( f_\theta \)

Initialize variables \( \theta \)

for \( epoch \in \{1,2,\ldots,E\} \) do

Get mini-batch \( x,y \) from \( X \)

\( \tilde{x} = x + \text{Uniform}[-\epsilon, +\epsilon] \)

for \( i=1,2,\ldots,a \) do

\( \tilde{x} = \tilde{x} + \alpha \cdot \text{sign}(\nabla_x L_{attr}(\tilde{x},y)) \)

\( \tilde{x} = \text{Proj}_{\epsilon}(\tilde{x}) \)

end

\( i^* = \text{ground truth index} \)

\( j^* = \arg \max_j \text{logit}_j \)

Calculate \( g1 = \nabla_x (f(\tilde{x}),y) \)

Calculate \( g2 = \nabla_x (f(\tilde{x}),\cdot) \)

Calculate \( loss = L_{ce}(\tilde{x},y) + \lambda \cdot L_{attr}(\tilde{x}) \)

Update \( \theta \) using (loss)

end

return \( f_\theta \).

end

The optimization of \( L_{attr} \) involves computing gradient of \( g_i(x) \) with respect to input \( x \) which suffers from the problem of vanishing second derivative in case of relu activations, i.e. \( \partial^2 f_i / \partial x^2 \approx 0 \). To alleviate this, while optimizing \( L_{attr} \), we replace relu with softplus non-linearities \([18]\), as it has well-defined second derivative. The softplus approximates to relu as the value of \( \beta \) increases. After the training is complete, we perform and report all our results on the model with the relu activation neural network.

\[
\text{softplus}_\beta(x) = \frac{\log(1 + e^{\beta x})}{\beta}
\]

Psuedo-code for our training methodology is given in Algorithm 1. Note that other attribution methods can also be used (e.g. Integrated gradient\([59]\)) in our formulation of \( L_{attr} \).
3.3. Connection between Robustness and Interpretability

It was shown by authors of [24, 60] that classification models are vulnerable to small imperceptible adversarial perturbations $\delta$ which when added to $x$ drastically changes the model’s prediction. Such perturbed images are referred to as adversarial examples and are calculated by optimizing the following:

$$x_{adv} = \arg \max_{x:||x-z||_p<\epsilon} L_{ce}(\theta, \tilde{x}, y)$$  \hspace{1cm} (5)

where $L_{ce}$ is cross entropy loss and the perturbation is constrained by a $p$ norm to ensure that the perturbed example is perceptually close to the original sample.

Recently, it was observed by Tsipras et al.[61] that an adversarially robust model has salient gradients $g_i(x)$ i.e. saliency map highlights the perceptually relevant features of the image well and in turn looks similar to the image $x$. For classifiers satisfying locally affine approximation using relu activations, Etmann et al. [21] derive theoretical connection between adversarial robustness and the alignment of $g_i(x)$ with image $x$. We can quantify adversarial robustness for $x$ as it’s distance to the nearest decision boundary $\rho(x)$. For classifiers with sufficiently large locally affine region, we can upper bound $\rho(x)$ by $\hat{\rho}$:

$$\hat{\rho}(x) = \min_{j \neq i} \frac{f_\theta(x)_i - f_\theta(x)_j}{||g_i(x) - g_j(x)||}$$  \hspace{1cm} (6)

The index $j$ for which the RHS of equation 6 is minimum is denoted as $j^*$. Etmann et al. proved that $\hat{\rho}(x)$ is upper bounded by the alignment between $x$ and $g_{j^*}(x)$, i.e.

$$\hat{\rho}(x) \leq x \frac{(g_{j^*}(x) - g_{j^*}(x))}{||g_{j^*}(x) - g_{j^*}(x)||} + E_1$$

$$\leq x \frac{g_{j^*}(x)}{||g_{j^*}(x)||} + E_2$$  \hspace{1cm} (7)

We note that the alignment of attribution maps with image $x$ used in the formulation of $L_{attr}$ also comes up in the above inequality.

3.4. Extension to Weakly supervised Object localization (WSOL)

The problem of WSOL deals with detecting objects where only class level data regarding images are available, and ground truth bounding box data is inaccessible. Generally, the pipeline for obtaining bounding box locations in WSOL relies on the attribution maps. Therefore, several methods [15, 81, 80] modify the training procedure of the classifier to obtain better attribution maps that covers the whole object in the image. Since, the aim of our training methodology is to provide robust attribution maps for the models, we think testing our proposed model in this problem setting seems relevant. Indeed, that seems to be the case as our proposed model achieves the new state-of-the-art localization results on CUB dataset.
4. Experiments and Results

4.1. Attributional and Adversarial Robustness

Baseline. We compare our training methodology with the following approaches:

- Natural: Standard training with minimization of cross entropy classification loss.
- PGD-\(n\): Adversarially trained model with \(n\) step PGD attack as in [37].
- IG Norm and IG-SUM Norm [14]: This is the current state-of-the-art training technique for attributional robustness that aims at making model’s integrated gradient saliency map robust.

Implementation Details. To show the efficacy of our methodology, we benchmark on the following standard vision datasets: CIFAR-10[34], SVHN[41], GTSRB[58] and Flower [42].

For CIFAR-10, GTSRB and Flower dataset we use Wideresnet-28-10 [72] model architecture for all approaches, i.e natural, sal and PGD-10 and for SVHN dataset we use WideResNet-40-2 [72] architecture. The perturbation for our training methodology and PGD-\(n\) training is \(\ell_\infty\) bounded with \(\epsilon = 8 / 255\) for all datasets. We use \(\lambda = 0.5\), \(\alpha = 3\) and \(\beta = 50\) for all the experiments in this paper. We use SGD optimizer while training with a step wise learning rate schedule. More details about the dataset and training can be found in appendix A.

Evaluation: To evaluate attributional robustness of models, we perform attribution attack using formulation of Ghorbani et al. [23] for fair comparison with [14]. The attack objective is as follows:

\[
\hat{x} = \arg \max_k - \sum_{k \in B} I(\hat{x}, f(\hat{x})_k)
\]

subject to: \(\|\hat{x} - x\|_\infty < \epsilon\) (8)

Here, \(I(x, f(x)_k)\) is the attribution map calculated using Integrated Gradient[59] method and \(B\) is the set of top-\(k\) indices of attribution map of image \(x\). We optimize for the above objective using iterative projected gradient descent method. We set \(k\) in top-\(k\) as 1000 for flower dataset and 100 for the rest of the datasets following [14]. All other hyper-parameters used in evaluation are also same as [14].

Similarity measure: For assessing similarity between attribution map of \(x\) and \(\hat{x}\) we use the following three metrics as metrics as mentioned in [14]: Top-\(k\) intersection (IN); Kendall’s tau coefficient (K); and Spearman correlation (S). Kendall’s tau and Spearman correlation are a measure of similarity in ordering when ranked by the values and therefore are suitable metrics for attribution maps. Top-\(k\) inter-
Table 3: Results of weakly supervised segmentation on Flower dataset. Grad: Gradients; IntGrad: Integrated Gradients.

| Model     | Saliency Method | Grad | IntGrad | GradCAM++ |
|-----------|-----------------|------|---------|------------|
| Natural   | Grad            | 0.2441 | 0.3372 | 0.0200     |
| PGD-7 [37]| IntGrad         | 0.2465 | 0.4222 | 0.1097     |
| Ours      | GradCAM++       | 0.3172 | 0.6038 | 0.0849     |

4.1.1 Weakly Supervised Image Localization

This task relies on the saliency map obtained from the classification model to estimate a bounding box for objects. We compare our approach with ADL[15] on CUB dataset which has ground truth bounding box of 5794 bird images.

We adopt a similar approach as ADL for extracting bounding boxes except that we use gradient attribution map \( \nabla_x(f(x)_p) \) instead of CAM [82]. As a post-processing step, we convert the attribution map to grayscale, normalize it and then apply a mean filtering of \( 3 \times 3 \) kernel over it. Then a bounding box is fit over this heatmap to localize the object. We perform experiments on Resnet-50 [26] and VGG [54] architecture and report the results in Table 2. We use the same evaluation metrics as used in [15] i.e. Top-1 classification accuracy (Top-1 Acc) : Localization accuracy when ground truth is known (GT-Known Loc), i.e when intersection over union (IoU) of estimated box and ground truth bounding box >0.5; Top-1 localization accuracy, i.e. when prediction is correct and IoU of bounding box >0.5 (Top-1 Loc). Model trained with our approach results in highest GT-Known Loc and Top-1 Loc for both Resnet-50 and VGG-GAP [15] model with gradient saliency method [53]. We use \( l_\infty \) bound of \( \epsilon = 2/255 \) for our training methodology and PGD-7 training on CUB dataset. We also show a qualitative evaluation comparing the bounding box estimated by our approach with [15] in figure 3. More examples images are shown in Appendix A. For training the models, we use a SGD optimizer with a step-wise learning rate schedule as mentioned in [15].

5. Discussion and Ablation Studies

To understand the scope and impact of the proposed approach, we perform various experiments and report these findings in this section. We choose CIFAR-10 as the primary dataset for the following experiments.

Robustness to targeted attribution attack In targeted attribution attack, the aim is to calculate perturbations that
minimize the dissimilarity between the attribution maps of given two images. We evaluate the attributional robustness of our proposed model in targeted attribution attack setting [18] using the attribution method [59]. For getting targeted attribution map we randomly shuffle a batch of 1000 test set examples and evaluate our method and PGD-10 trained model on this set. The Kendall’s tau coefficient and top-k intersection similarity measure of original and perturbed image on our model was 64.76 and 70.64 as compared to 36.29 and 31.81 on PGD-10 model. The higher correlations for model trained via our approach reflects the efficacy of our approach in targeted attribution attack setting.

Image Segmentation Image segmentation is an important vision task for which collecting training data annotations can easily prove to be time-consuming and costly. Therefore, recent works [33, 64, 65, 30, 44, 77, 43] in weakly supervised segmentation are focusing on training models using weaker annotations like image labels instead of ground-truth segmentation masks. We show that as the model becomes robust to adversarial and attributional attacks, the saliency maps can act as a better prior for segmentation masks. We show this on flower dataset where we have access to ground-truth segmentation masks of 849 images. We evaluate our results using Top-1 Seg metric which is analogous to the Top-1 Loc metric used in weakly supervised localization in Section 4.1.1. Top-1 Seg considers an answer as correct when the model prediction is correct and the IoU of ground-truth mask and estimated mask is atleast 50%. We compare our approach against natural and PGD-7 trained models using three different saliency methods: gradients[53], Integrated Gradients [59] and GradCAM++[13] in table 3. Saliency maps are converted into gray-scale heatmap and a smoothing filter\(^2\) is applied as a post-processing step. Example images of weakly-supervised segmentation masks generated by above models and explanation methods can be seen in figure 4. From table 3, we can see that our approach generally outperforms the Natural and Madry (PGD-7) on different attribution techniques.

Robustness to various common perturbation [27] and spatial adversarial perturbation [20]. We compare our proposed model with PGD-10 on the common perturbations dataset released by Hendrycks et al. [27] for CIFAR-10. The dataset consists of perturbed images with 75 commonplace visual perturbations at varying intensity levels. Our model achieves better generalization than other models on almost all perturbations as shown in table 4. We also perform comparison on spatial attack by Engstrom et al. [20] and observe robustness of 11.13% and 6.76% for our model and PGD-10 trained model respectively.

Robustness to stronger attacks To show the absence of gradient masking and obfuscation [10, 7], we evaluate our model on a gradient free adversarial optimization algorithm [63] and a higher iteration PGD attack. We observe similar adversarial robustness when we increase the number of steps in PGD-attack. For 100 step and 500 step PGD attack we achieve 37.42% and 37.18% accuracy respectively. On SPSA [63] attack our model and PGD-10 trained model obtains 46.7 and 55.61 adversarial accuracy respectively. We report the SPSA [63] attack results over 1000 random samples from test set.

Effect of $\beta$ and $\lambda$ on Performance We fix the values of $\lambda$ to 0.5, $a$ to 3 (best-performing values) and train the model for different values of $\beta$. The left plot in Fig 5 shows the influence of the $\beta$ in the performance (i.e. Test Accuracy and Adversarial accuracy on PGD-40 perturbations) of the model. It can be observed from the plot that initially, adversarial accuracy increases with increasing $\beta$, but the trend reverses for higher values of $\beta$. However, the test accuracy increases with increasing $\beta$. The left plot in Fig 6 shows attributional robustness of models with varying $\beta$. Here, we observe a similar trend that initially the attributional robust-

\(^2\)https://pillow.readthedocs.io/en/5.1.x/reference/ImageFilter.html
ness increases till $\beta = 100$ and then decreases. To examine the role of soft-margin triplet loss on the proposed training methodology, we fix $\beta$ to 50, $a$ to 3 and train the model for different values of $\lambda$. The hyperparameter $\lambda$ controls the ratio of weight assigned to the classification loss and the soft-margin triplet loss. The middle plot in Fig 5 and 6 show the results of this experiment. We find that the attributional and adversarial robustness of model increases with increasing $\lambda$ and saturates at 0.75. However, we observe that the test accuracy starts to suffer as the magnitude of $\lambda$ increases.

**Effect of $a$ on Performance** We analyze the effect of attribution attack steps $a$ for our proposed training methodology. We fix $\lambda$ to 0.5, $\beta$ to 50 and vary attack steps $a$ to examine the performance. We find that the performance in terms of test accuracy, adversarial accuracy and attributional robustness saturates or decreases after $a = 3$ as showed in the right plot of Fig 5 and 6.

**Qualitative evaluation of attribution maps** We observe that the proposed model shows visually semantic attribution map obtained via [53] in figure 7. We note that, similar remarks were also made for adversarially trained models in [61].

**Attributional Robustness** In Fig 8, we show the variance box plot of attributional robustness measure on Kendall Correlation and Top-k Intersection for naturally trained, our model and adversarially trained PGD-10 [37] model. The configuration for evaluating the attributional robustness is same as mentioned in [14].

**Evaluation of Cosine between $x$ and $\nabla_x f(x)_y$** In Fig 9, we show the statistics of the cosine of $x$ and $\nabla_x f(x)_y$ on the test set for CIFAR-10 for different models. We observe that our proposed approach has the highest alignment between the image $x$ and its saliency map [53]. For naturally trained model, the cosine measure is particularly low when compared with adversarially trained (PGD-10) [37] and our model.

Using $L_{attr} + L_{adv}$ to calculate attribution distorting examples $\tilde{x}$ With the motive to combine the benefits from attributional and adversarial robust model, we augment the loss function our approach with adversarial loss [37] also. We observe that the model achieves an adversarial accuracy of 52.31 with test accuracy of 85.33. However, the attributional robustness measure of Top-k intersection and kendall correlation using integrated gradients decreases to 74 and 77 from 92.9 and 91.76 respectively.

**6. Conclusion**

We observed that increasing the alignment between the input and the saliency map generated from the network’s prediction leads to improvement in the attributional robustness. We empirically showed this for both un-targeted and
targeted attribution attacks over several benchmark datasets. We showed that the attributional robustness also brings out other improvements in the network, such as reduced vulnerability to adversarial attacks and common perturbations. For other vision tasks such as weakly supervised object localization and segmentation, our attributionally robust model achieves a new state-of-the-art accuracy even without being explicitly trained to achieve that objective. Furthermore, given the improvements in other vision tasks, we believe that attributional robustness is an essential area of research in computer vision domain, and we hope that our work can open a discussion around this broader notion of robustness.

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Appendix

A. Attributional Robustness: Dataset and Implementation Details

In this section, we describe the datasets and model hyperparameters used in attributional robustness experiments.

SVHN [41]: Data and Model: SVHN consists of images of digits obtained from house numbers in Google Street View images, with 73257 digits for training and 26032 digits for testing over 10 classes. We perform experiments on SVHN using WideResNet-40-2 [72] architecture for training on reported approaches.

Hyperparameters for Training:

Natural: We use SGD optimizer with an initial learning rate of 0.1, momentum of 0.9, $l_2$ weight decay of $2\times10^{-4}$ and batch size of 128. We train it for 200 epochs with a learning rate schedule decay of 0.1 at 50th, 80th and 0.5 at 150th epoch.

PGD-7[37]: We use the training configuration as mentioned in (cifar-10 challenge) to perform 7-step adversarial training with $\epsilon = 8./255$.

Our Approach: We use the same training configuration as mentioned in Natural model with $\beta = 50$ and $\lambda = 0.5$. We calculate $\tilde{x}$ using $\epsilon = 8./255$ and $a = 3$.

CIFAR-10 [34] Data and Model: It consists of 50000 training images for 10 classes with resolution of $32 \times 32 \times 3$. We normalize the images with its mean and standard deviation for training. We train a WideResNet28-10 [72] model for all the experiments on this dataset.

Hyperparameters for Training:

Natural: We use SGD optimizer with an initial learning rate of 0.1, momentum of 0.9, $l_2$ weight decay of $2\times10^{-4}$ and batch size of 128. We train it for 200 epochs with a learning rate schedule decay of 0.1 at 50th, 80th and 0.5 at 150th epoch.

PGD-10[37]: We use the training configuration as mentioned in [38] to perform 10-step adversarial training with $\epsilon = 8./255$.

Our Approach: We use the same training configuration as mentioned in Natural model with $\beta = 50$ and $\lambda = 0.5$. We calculate $\tilde{x}$ using $\epsilon = 8./255$ and $a = 3$.

GTSRB [58]: Data and Model: German Traffic Signal Recognition Benchmark [58] consists of 43 classes of traffic signals with 34,799 training images, 4,410 validation images and 12,630 test images. We resize the images to $32 \times 32 \times 3$ and normalize the images with its mean and standard deviation for training. To balance the number of images for each class, we use data augmentation techniques consisting of rotation, translation, and projection transforms to extend the training set to 10,000 images per class as in [14]. We train WideResNet28-10 [72] model for carrying out experiments related to this dataset.

Hyperparameters for Training:

Natural: We use SGD optimizer with an initial learning rate of 0.1, momentum of 0.9, $l_2$ weight decay of $2\times10^{-4}$ and batch size of 128. We train it for 12 epochs with a learning rate schedule decay of 0.1 at 4th, 6th and 0.5 at 10th epoch.

PGD-7[37]: We use the training configuration as mentioned in (cifar-10 challenge) to perform 10-step adversarial training with $\epsilon = 8./255$.

IG Norm and IG-Sum Norm [14]: We report the accuracy as mentioned in the paper [14].

Our Approach: We use the same training configuration as mentioned in Natural model with $\beta = 50$ and $\lambda = 0.5$. We calculate $\tilde{x}$ using $\epsilon = 8./255$ and $a = 3$.

Flower [42]: Data and Model: It is a 17 category flower dataset with 80 images for each class. We resize the images to $128 \times 128 \times 3$ and normalize it with its mean and standard deviation for training. The training set consists of 1,224 images with 72 images per class. The test set compromises of 136 images with 8 images per class. We use standard data augmentation techniques of rotation, translation, and projection transforms to extend the training data so that each class contains 1,000 training examples as proposed in [14]. We use WideResNet28-10 [72] model for the reported approaches.

Hyperparameters for Training:

Natural: We use SGD optimizer with an initial learning rate of 0.1, momentum of 0.9, $l_2$ weight decay of $2\times10^{-4}$ and batch size of 128. We train it for 68 epochs with a learning rate schedule decay of 0.1 at 15th, 35th and 0.5 at 50th epoch.

PGD-7[37]: We use the training configuration as mentioned in (cifar-10 challenge) to perform 7-step adversarial training with $\epsilon = 8./255$.

IG Norm and IG-Sum Norm [14]: We report the accuracy as mentioned in the paper [14].

Our Approach: We use the same training configuration as mentioned in Natural model with $\lambda = 0.5$ and $\beta = 50$. We calculate $\tilde{x}$ using $\epsilon = 8./255$ and $a = 3$.

B. Weakly Supervised Localization: Dataset and Implementation Details

In this section, we provide details of the dataset and model hyper-parameters used for the results presented in
Figure 10: Examples of estimated bounding box and heatmap by ResNet50 model trained via our approach on randomly chosen images of CUB dataset; Red bounding box is ground truth and green bounding box corresponds to the estimated box.

the main paper.

Dataset and Model: CUB [67] is an image dataset of 200 different bird species (mostly North American) with 11,788 images in total. The information as a bounding box around each bird is also available. We finetune a ResNet-50 [26] model pretrained on ImageNet for the reported approaches as in [15].

Hyper-parameters for training

Natural: We use SGD optimizer with an initial learning rate of 0.01, momentum of 0.9 and $l_2$ weight decay of $1e^{-4}$. We train the model for 200 epochs with learning rate decay of 0.1 at every 60 epochs.

PGD-7 [37]: We use same hyper-parameters as natural training with $\epsilon = 2./255$, and step size = $0.5/255$ for calculating adversarial examples.

Our Approach: We use SGD optimizer with an initial learning rate of 0.01, momentum of 0.9 and $l_2$ weight decay of $2e^{-4}$. We decay the learning rate by 0.1 at every 40 epoch till 200 epochs. While calculating $L_{attr}$ loss, we took mean over channels followed by an average pool of $3 \times 3$ kernel for both images and gradients. Values of other hyper-parameters are $\epsilon = 2./255$, step size = $1.5/255$, $a = 3$, $\lambda = 0.5$ and $\beta = 50$.

B.1. Qualitative analysis

Fig 10 shows the estimated bounding box and heatmap derived from gradient based attribution [53] on randomly sampled images for ResNet50 model trained via our approach. From the figure 10, we observe that the estimated bounding box sometimes does not capture the object in cases where birds have extended wings, or the bird is in an occluded area with branches and twigs.