Untapped Potential of Data Augmentation: A Domain Generalization Viewpoint

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Abstract

Data augmentation is a popular pre-processing trick to improve generalization accuracy. It is believed that by processing augmented inputs in tandem with the original ones, the model learns a more robust set of features which are shared between the original and augmented counterparts. However, we show that is not the case even for the best augmentation technique. In this work, we take a Domain Generalization viewpoint of augmentation based methods. This new perspective allowed for probing overfitting and delineating avenues for improvement. Our exploration with the state-of-art augmentation method provides evidence that the learned representations are not as robust even towards distortions used during training. This suggests evidence for the untapped potential of augmented examples.

1. Introduction

Contemporary learning algorithms demonstrate strong performance, even surpassing humans at times, when training and testing on similar distributions. Notwithstanding performance under such setting, they are far from human level robustness when evaluated under data shifts (Geirhos et al., 2018; Hendrycks & Dietterich, 2019; Mu & Gilmer, 2019). This problem is of central focus in learning distributionally robust models. While the related problem of robustness to imperceptible adversarial examples has received much larger interest (Madry et al., 2018); there has been an increasing push toward expanding the definition of robustness to include naturally occurring corruptions (Engstrom et al., 2019). This is especially so because best defenses against the narrow focused, adversarial examples does much worse with robustness to natural corruptions (Hendrycks et al., 2019).

Data augmentation technique is widely adopted for image preprocessing and has recently been shown to improve out-of-domain robustness (Hendrycks et al., 2019). It is, however, unclear how the augmented examples interact with the clean examples. Training under data augmentation resembles multi-source training of DG. An ideal DG algorithm exploits the train time domain variation so as to learn a hypothesis that is better equipped at generalizing to new domains. The Expected Risk Minimization (ERM) baseline on the other hand does not attend to the domain boundaries and yields bad domain-shift robustness owing to overfitting.

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We make the following contributions.

- **Untapped potential**: We show that the standard augmentation (including state-of-art) methods underutilize augmented examples by overfitting on them.
- **Future direction**: We note that there is a broad scope for improving augmentations for even better robustness and conclude with a discussion of future line of work for improving augmentations for even better robustness.

## 2. Untapped Potential of Augmentations

In this section, we provide evidence of augmentation overfit by systematically exploring a recent state-of-art augmentation method. As a case study, we use models trained with AugMix (Hendrycks et al., 2019) when trained on CIFAR-10, CIFAR-100 and ImageNet across different network architectures.

Augmentation is a standard trick employed to improve generalization, dominantly in image applications. In the extreme case of catastrophic overfitting of the augmentations, the augmented examples cannot help generalize better on the original examples. On the other extreme, in the ideal scenario, we expect the algorithm to draw what is common between the clean and augmented examples without having to employ any specific features for either clean or augmented data. Vanilla augmentation need not lead to the ideal scenario of learning common features between clean and augmented inputs. For example, Vasiljevic et al. (2016) report that train-time blur augmentations do not generalize to unseen blurs. Furthermore multiple DG studies (Motiyan et al., 2017; Ghifary et al., 2015) show that train data containing instances under multiple rotations does not generalize to unseen rotations. In practice, standard augmentation falls in between the two extremes of catastrophic overfitting and perfect parameter sharing.

We pose the question of how much feature sharing occurs between the clean and augmented examples with AugMix using measures borrowed from the DG literature. In section 2.1, we probe how domain invariant are the representations obtained from various layers. Section 2.2 employs a recent common-specific decomposition strategy proposed in Piratla et al. (2020) to identify any augmentation-specific (overfitting) components in the model weights. Finally in section 2.3, we make a more controlled evaluation of the generalization to augmentations of varying severity levels.

### 2.1. Domain Divergence Measure

Domain overfit can be qualitatively measured by looking at how transferable the parameters are between the train domains. The seminal paper on domain adaptation: Ben-David et al. (2006), proved an upper bound on generalization gap between any two domains in terms of a domain divergence metric. Equation 1 provides this metric for a given hypothesis class \( \mathcal{H} \) and source and target distributions: \( S, T \) with their respective populations: \( n, n' \).

\[
\begin{align*}
d_{\mathcal{H}}(S, T) &= 2(1 - \min_{\eta \in \mathcal{H}} \{ \frac{1}{n} \sum_{i=1}^{n} I[\eta(x_i) = 0] \\ &+ \frac{1}{n'} \sum_{i=n+1}^{n+n'} I[\eta(x_i) = 1] \})
\end{align*}
\]

Intuitively, the domain divergence would be low when the hypothesis class induced by the learned representations do not allow for domain prediction i.e. the representations should be domain invariant. Since it is hard to compute the divergence measure exactly, a proxy measure, accuracy of a trained discriminator proposed in Ganin et al. (2016), is adopted. We train a domain discriminator to discriminate augmented examples from clean examples. Higher the accuracy of the domain discriminator, greater is the domain overfit.

We probe for domain invariance of the representations learned by AugMix on CIFAR and ImageNet datasets. We use representations from two different layers: the penultimate and antepenultimate layers, penultimate layer is the layer before the softmax layer. The train data for the discriminator is collated from the representations of the clean \( (x_c) \) and augmented \( (x_a) \) examples along with their domain assignment: \( \bigcup_{i} \{ x_{ci}, 0 \} \cup \{ x_{ai}, 1 \} \). A linear discriminator is then trained on 40,000 examples with equal proportion of clean and augmented. If the model learns generalizable common features, then information related to the augmentation’s distortion should be minimal. On the other hand if the model relies on domain specific feature, that information will be present in the representation layers of the model. The same information can be used to correctly identify the domain of the input sample.

Table 1 shows the discriminator’s performance for a range of
models trained with AugMix. We report discrimination accuracy on unseen test examples that are similarly collected as train and shown in parenthesis is the train accuracy. The domain predictive accuracy in the penultimate layer is close to random, however, in just the neighboring antepenultimate layer it is possible to perfectly discern if the representation is from a clean or augmented example. The prevalence of domain identifying information up until this layer is indicative of shallow parameter sharing between augmentations and clean examples. This highlights the need for measures that promote higher parameter sharing between augmentations and original instances.

2.2. Common vs Specialized Components of the Classifier

When training on multi-domain data, we desire to retain only the components of the classifier that rely on features that are common between the domains. This concept is related but different from domain-invariant representations. While domain-invariant representations require that the features are invariant between the domains, the decomposition method of Piratla et al. (2020) encourages features of consistent label-correlation between the domains. The latter thereby is less restrictive than domain invariant features. The presence of domain-specific components in the classifier hurts out-of-domain generalization and when fixed can readily translate to even better robustness (Piratla et al., 2020). Further, by employing the decomposition procedure from their work and comparing the support of domain specific component vs the common component of the classifier, we can qualitatively comment on the robustness strength.

In order to study if AugMix suffers from the presence of any domain specific components, we employ the common-specific decomposition on the trained checkpoints. We obtain penultimate layer representations for a randomly sampled 20,000 train examples of original and augmented images each. We then obtain optimal content-label classifier individually for clean and augmented instances. These are denoted as $w_{\text{clean}}, w_{\text{aug}}$ respectively. We are interested in decomposing these parameters in to a linear combination of common ($w_c$) and domain-varying ($w_s$) component accompanied by domain-specific combination parameter ($\gamma_{\text{clean}}, \gamma_{\text{aug}}$). This requires solving the following constrained problem shown in Equation block 2.

\[
\begin{align*}
    w_{\text{clean}} &= w_c + \gamma_{\text{clean}} w_s \\
    w_{\text{aug}} &= w_c + \gamma_{\text{aug}} w_s \\
    w_c \perp w_s
\end{align*}
\]

Note from the decomposition problem that (1) contribution of the common component $w_c$ to each of $w_{\text{clean}}, w_{\text{aug}}$ is the same, and (2) the contribution of specific component $w_s$ varies. In the ideal case when the representation contains only features of consistent label correlations between domains, then the domain specific components ($\gamma_{\text{clean}} w_s, \gamma_{\text{aug}} w_s$) are diminutive compared to the common component ($w_c$). On the other hand when the representations contain features that favor only one of the two domains, it manifests in strong domain specific components.

In Table 2, we report the ratios of norms of specific and common components over a range of models trained with AugMix, expression for the reported measure shown below:

\[
\frac{\| \gamma_{\text{clean}} w_s, \gamma_{\text{aug}} w_s \|}{\| w_c, w_c \|}
\]

where $[\cdot]$ denotes concatenation of the vectors and $\| \cdot \|$ represents the Frobenius norm.

Ideally the ratio is expected to be very close to zero as the specific components are negligible. However, for a range of AugMix trained models, the ratio is significantly non-zero implying that there is non-negligible support for specific components compared to the common component. This strongly suggests the scope for better robustness when fixed\(^2\). Interestingly, note that the corruption error (not shown here) and the specific-common ratio are inversely proportional on same dataset but different architecture.

2.3. Controlled Evaluation of Distributional Robustness

In this section, inspired from Geirhos et al. (2018); Vasiljevic et al. (2016), we make a controlled evaluation of the AugMix trained models in order to objectively measure domain sensitivity. AugMix allows for several knobs on the train time augmentations; Of our particular interest are (1) mixing coefficient that combines the augmented example with the original example (2) severity level of distortions for input transformation. We make a more modest evaluation on the test set using only the seen distortions but with differing distortion severity and with or without mixing with clean examples.

Table 3 summarizes our findings. Without mixing means we evaluate on the augmented example directly. AugMix draws several samples from the convex combination of clean and distorted examples, and thereby we expect generalization to any convex combination of clean and augmented examples including either extremes. However, it is surprising that we found consistent drop in accuracy with the default severity level of 3 and when evaluated on an endpoint: distorted

\(^2\)However in our case, post-processing linear classifier of the checkpoints to only retain the common component worsened the mean corruption error. Would be more interesting to evaluate the decomposition during the train time following Piratla et al. (2020)
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| Layer | Arch | CIFAR-10 | CIFAR-100 | ImageNet |
|-------|------|---------|----------|----------|
|       | AC   | WRN     | AC       | WRN      | ResNet-50 |
| PL    | 50.2 (52.8) | 51.9 (52.3) | 52.3 (52.1) | 51.0 (50.8) | 54.5 (57.4) |
| APL   | 100 (100)   | 85.5 (91.8) | 100 (100)   | 84.8 (86.8) | 76.8 (84.0) |

Table 1. Test and train domain discrimination accuracy (train accuracy shown in brackets) on CIFAR-10, CIFAR-100 and ImageNet. PL and APL stands for penultimate and antepenultimate layers. AC and WRN denote AllConv and WideResNet architecture respectively.

| Dataset | Arch | AC | WRN | RN-50 |
|---------|------|----|-----|-------|
| CIFAR-10 | 0.6  | 0.4 | -   |       |
| CIFAR-100 | 0.5  | 0.2 | -   |       |
| ImageNet | -    | -   | 0.5 |       |

Table 2. Ratio of norm of specific components to common components, smaller the better, for CIFAR-10, CIFAR-100 with AllConv (AC) and WideResNet (WRN) architecture, ImageNet with ResNet-50 (RN-50) architecture.

Also, we draw attention to the drop in accuracy when using severity level of 5 just outside of the train time value of 3. These observations highlight the fragile robustness of AugMix.

| Test | CIFAR-100 | CIFAR-10 |
|------|-----------|----------|
| Mix  | 71.2      | 92.6     |
| wo Mix | 69.9 (0.1) | 65.4 (0.3) |
| s=3  | 91.8 (0.1) | 88.9 (0.1) |
| s=5  | 66.8 (0.3) | 61.4 (0.4) |
|      | 90.1 (0.2) | 87 (0.1)  |

Table 3. Classification accuracy of AugMix trained on CIFAR-100 and CIFAR-10 when evaluated on seen distortions of varying severity level (rows) and with (Mix) or without mixing (wo Mix) with clean example. The row corresponding to Test denotes performance on clean test set.

4. Discussion

Standard training on clean and augmented examples combined need not realize the full potential of augmentations. Deep neural networks can learn unexpected properties and overfit on augmentations without delivering on the desired generalization.

AugMix (Hendrycks et al., 2019), samples distortions from a large pool making it harder to overfit on a non-fixed set of distortions. The intent is to force learning of only features that transfer between clean and augmented examples. However, we present evidence in our work that contradicts this idealistic scenario of feature or parameter sharing with augmentations. On a range of datasets and architectures, AugMix employs specialized features for augmented examples as indicated by the domain divergence measure and common-specific decomposition of the classification layer. The utilization of specialized features could hinder out-of-domain generalization.

Controlled evaluation on distortions obtained from slightly different distortion sampling parameters expose the fragile robustness to unseen but easy distortions. Furthermore the model retains sensitivity to training parameters. The mixing operation used in Augmix would lead one to expect that the model is robust on the simplex between clean data and its augmentations. However contrary to expectations even on the training augmentations, one sees significant difference between different mixing patterns. The fact that the models are not as robust as believed, suggests there is still significant scope of improvement from the way augmentations are currently utilized.

We envision future work targeting the patterns observed in this work. Mitigation of specific components in the representations can be achieved by adopting methods from Piratla et al. (2020); Sanyal et al. (2020). Parameter sharing can be further promoted through a systematic study of domain invariant networks (Ganin et al., 2016).

3Augmix severity scale is from 0 to 10
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