## **Asymmetric Loss For Multi-Label Classification**

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#### **Abstract**

In a typical multi-label setting, a picture contains on average few positive labels, and many negative ones. This positive-negative imbalance dominates the optimization process, and can lead to under-emphasizing gradients from positive labels during training, resulting in poor accuracy. In this paper, we introduce a novel asymmetric loss ("ASL"), which operates differently on positive and negative samples. The loss enables to dynamically down-weights and hard-thresholds easy negative samples, while also discarding possibly mislabeled samples. We demonstrate how ASL can balance the probabilities of different samples, and how this balancing is translated to better mAP scores. With ASL, we reach state-of-the-art results on multiple popular multi-label datasets: MS-COCO, Pascal-VOC, NUS-WIDE and Open Images. We also demonstrate ASL applicability for other tasks, such as single-label classification and object detection. ASL is effective, easy to implement, and does not increase the training time or complexity.

Implementation is available at: https://github.com/Alibaba-MIIL/ASL.

#### 1. Introduction

Typical images contain multiple objects and concepts [35], highlighting the importance of multi-label classification for real-world tasks. Recently, remarkable strides have been made in multi-label benchmarks such as MS-COCO [22], NUS-WIDE [7], Pascal-VOC [12] and Open Images [19]. Notable success was reported by exploiting label correlation via graph neural networks which represent the label relationships [6, 5, 11] or word embeddings based on knowledge priors [6, 32]. Other approaches are based on modeling image parts and attentional regions [37, 13, 33, 36], as well as using recurrent neural networks [25, 30].

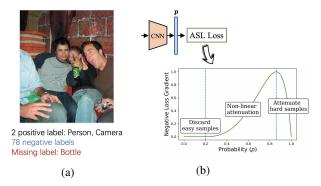


Figure 1: (a) **Real world challenges in multi-label classification**. A typical image contains few positive samples, and many negative ones, leading to high negative-positive imbalance. Also, missing labels in ground-truth are common in multi-label datasets. (b) **Proposed solution with ASL**. Our model is based on a standard architecture and no external information is required. The loss properties will be detailed in Section 2.5

Despite their effectiveness, recent approaches are characterized by complex architecture modifications and relying on additional external information, such as word embeddings and NLP models. In this work, we question whether such complicated solutions are truly necessary for achieving high performance in multi-label classification tasks. In particular, we demonstrate that careful design of the loss function can greatly benefit classification accuracy, while still maintaining the simplicity of a solution based on a standard architecture, with no additional reliance on external information.

A key characteristic of multi-label classification is the inherent class imbalance created when the overall number of labels is large. By nature, most images contain only a small fraction of the labels, implying that the number of positive samples per category will subsequently be much lower than the number of negative samples. To address this,

[34] suggested a loss function for handling the imbalance in multi-label problems. However, it was aimed specifically at long-tail distribution scenarios. High negative-positive imbalance is apparent also in dense object detection, where the imbalance stems from the ratio of foreground vs. background regions. A common solution is to adopt the focal loss [21], which further decays the loss as the label's confidence increases. This puts focus on hard samples, while down-weighting easy samples, which are mostly related to easy background locations.

Surprisingly, focal loss is seldom used for multi-label classification, and cross-entropy is often the default choice (see [6, 1, 4, 23, 13], for example). Since high negativepositive imbalance is also encountered in multi-label classification, focal loss might provide better results, as it encourages focusing on relevant hard-negative samples, which are mostly related to images that do not contain the positive class, but do contain some other confusing categories. Nevertheless, for the case of multi-label classification, treating the positive and negative samples equally, as proposed by focal loss, is sub-optimal, as it results in the accumulation of more loss gradients from negative samples, and down-weighting of important contributions from the rare positive samples. In other words, the network might focus on learning features from negative samples while underemphasizing learning features from positive samples.

In this paper, we introduce an asymmetric loss (ASL) for multi-label classification, which explicitly addresses the negative-positive imbalance. ASL is based on two key properties: first, to focus on hard negatives while maintaining the contribution of positive samples, we decouple the modulations of the positive and negative samples and assign them different exponential decay factors. Second, we propose to shift the probabilities of negative samples to completely discard very easy negatives (hard thresholding). By formulating the loss derivatives, we demonstrate that probability shifting also enables to discard very hard negative samples, suspected as mislabeled, which are common in multi-label problems [11].

We compare ASL to the common symmetrical loss functions, cross-entropy and focal loss, and show significant mAP improvement using our asymmetrical formulation. By analyzing the model's probabilities, we demonstrate the effectiveness of ASL in balancing between negative and positive samples. We also introduce a method that dynamically adjusts the asymmetry level throughout the training process, by demanding a fixed gap between positive and negative average probabilities, allowing simplification of the hyperparameter selection process.

The paper's contributions can be summarized as follow:

 We design a novel loss function, which explicitly copes with two main challenges in multi-label classification: high negative-positive imbalance and ground-truth mislabeling.

- We thoroughly study the loss properties via detailed gradient analysis.
- An adaptive procedure for controlling the asymmetry level of the loss is introduced to simplify the process of hyper-parameter selection.
- Using ASL, we obtain state-of-the-art results on four popular multi-label benchmarks. For example, we reach 86.6% mAP on MS-COCO dataset, surpassing the previous state-of-the-art by 2.8%.
- Our solution is effective and easy to use. It is based on a standard architecture, and no external information is required, in contrast to recent approaches.

## 2. Asymmetric Loss

In this section, we will first review cross-entropy and focal loss. Then we will introduce the components of the proposed asymmetric loss (ASL), designed to address the inherent imbalance nature of multi-label datasets. We will also analyze ASL gradients, provide probability analysis, and present a method to set the loss' asymmetry levels during training dynamically.

#### 2.1. Binary Cross-Entropy and Focal Loss

A general form of a binary loss applied on each output of the network is given by:

$$L = -yL_{+} - (1 - y)L_{-} \tag{1}$$

Where y is the ground-truth label and  $L_+$  and  $L_-$  are the positive and negative loss parts, respectively. Following [21], focal loss is obtained by setting  $L_+$  and  $L_-$  as:

$$\begin{cases}
L_{+} = (1-p)^{\gamma} \log(p) \\
L_{-} = p^{\gamma} \log(1-p)
\end{cases}$$
(2)

where p is the network's output probability and  $\gamma$  is the focusing parameter.  $\gamma = 0$  yields the binary cross-entropy.

By setting  $\gamma>0$  in Eq. 2, the contribution of easy negatives (having low probability,  $p\ll 0.5$ ) can be downweighted in the loss function, enabling to focus more on harder samples during training.

## 2.2. Asymmetric Focusing

When using focal loss for multi-label training, there is an inner trade-off: setting high  $\gamma$ , to sufficiently down-weight the contribution from easy negatives, may eliminate the gradients from the rare positive samples. We propose to decouple the focusing levels of the positive and negative samples. Let  $\gamma_+$  and  $\gamma_-$  be the positive and negative focusing parameters, respectively. We obtain asymmetric focusing by re-

defining the loss:

$$\begin{cases}
L_{+} = (1-p)^{\gamma_{+}} \log(p) \\
L_{-} = p^{\gamma_{-}} \log(1-p)
\end{cases}$$
(3)

Since we are interested in emphasizing the contribution of positive samples, we usually set  $\gamma_- > \gamma_+$ . Asymmetric focusing decouples the decay rates of positive and negative samples. Through this, we achieve better control over the contribution of positive and negative samples to the loss function, and help the network learn meaningful features from positive samples, despite their rarity.

It should be noted that methods which address class imbalance via static weighting factors were proposed in previous works [17, 9]. However, [21] found that those weighting factors interact with the focusing parameter, making it necessary to select the two together. In practice, [21] even suggested a weighting factor which favors background samples ( $\alpha=0.25$ ). Hence we chose to avoid adding static weighting factors, and subsequently control the asymmetry level via two separate focusing factors, which can dynamically compensate for the inherent positive-negative imbalance.

#### 2.3. Asymmetric Probability Shifting

Asymmetric focusing reduces the contribution of negative samples to the loss when their probability is low (soft thresholding). Since the level of imbalancing in multi-label classification can be very high, this attenuation is not always sufficient. Hence, we propose an additional asymmetric mechanism, probability shifting, that performs hard thresholding of very easy negative samples, i.e., it fully discards negative samples when their probability is very low. Let's define the *shifted probability*,  $p_m$ , as:

$$p_m = \max(p - m, 0) \tag{4}$$

Where the *probability margin*  $m \ge 0$  is a tunable hyperparameter. Integrating  $p_m$  into  $L_-$  of Eq.(2), we get an asymmetric probability-shifted focal loss:

$$L_{-} = (p_m)^{\gamma} \log(1 - p_m) \tag{5}$$

In Figure 2 we draw the probability-shifted focal loss, for negative samples, and compare it to regular focal loss and cross-entropy. From a geometrical point-of-view, we can see from Figure 2 that probability shifting is equivalent to moving the loss function to the right by a factor m, thus getting  $L_-=0$  when p < m. We will later show, via gradient analysis, another important property of the probability shifting mechanism - it can also reject mislabeled negative samples.

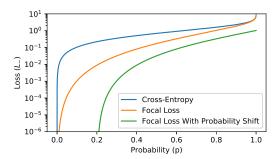


Figure 2: **Loss Comparisons.** Comparing probability-shifted focal loss to regular focal loss and cross-entropy, for negative samples. We used  $\gamma_- = 2$  and m = 0.2.

Notice that the concept of probability shifting is not limited to cross-entropy or focal loss, and can be used on many loss functions. Linear hinge loss [1], for example, can also be seen as (symmetric) probability shifting of linear loss. Also notice that logits shifting, as suggested in [21] and [34], is different from probability shifting due to the nonlinear sigmoid operation.

#### 2.4. ASL Definition

To define the Asymmetric Loss (ASL), we integrate the two mechanisms of asymmetric focusing and probability shifting into a unified formula:

$$ASL = \begin{cases} L_{+} = (1-p)^{\gamma_{+}} \log(p) \\ L_{-} = (p_{m})^{\gamma_{-}} \log(1-p_{m}) \end{cases}$$
 (6)

Where  $p_m$  is defined in Eq.(4). ASL allows us to apply two types of asymmetry for reducing the contribution of easy negative samples to the loss function - soft thresholding via the focusing parameters  $\gamma_- > \gamma_+$ , and hard thresholding via the probability margin m.

It can be convenient to set  $\gamma_+=0$ , so that positive samples will incur simple cross-entropy loss, and control the level of asymmetric focusing via a single hyper-parameter,  $\gamma_-$ . For experimentation and generalizability, we still keep the  $\gamma_+$  degree of freedom.

#### 2.5. Gradient Analysis

To better understand the properties and behavior of ASL, we next provide an analysis of the loss gradients, in comparison to the gradients of cross entropy and focal loss. Looking at the gradients is useful since, in practice, the network weights are updated according to the gradient of the loss, with respect to the input logit z. The loss gradients for neg-

ative samples in ASL are:

$$\frac{dL_{-}}{dz} = \frac{\partial L_{-}}{\partial p} \frac{\partial p}{\partial z}$$

$$= (p_{m})^{\gamma_{-}} \left[ \frac{1}{1 - p_{m}} - \frac{\gamma_{-} \log (1 - p_{m})}{p_{m}} \right] p(1 - p)$$
(7)

Where  $p = \frac{1}{1+e^{-z}}$ , and  $p_m$  is defined in Eq.(4). In Figure 3 we present the normalized gradients of ASL, and compare it to other losses. Following Figure 3, we can roughly split the negative samples in ASL into three loss-regimes:

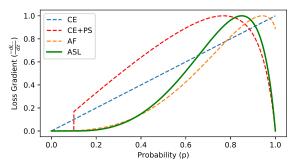


Figure 3: **Gradient Analysis.** Comparing the loss gradients vs. probability for different loss regimes. CE = Cross-Entropy  $(m=\gamma_-=0)$ , CE+PS = Cross-Entropy with Probability Shifting  $(m>0,\gamma_-=0)$ , AF = Asymmetric Focusing  $(m=0,\gamma_->0)$ , ASL  $(m>0,\gamma_->0)$ .

- 1. Hard-threshold very easy negatives, with p < m, that should be ignored, in order to focus on harder samples.
- 2. Soft-threshold negative samples, with p > m, that should be attenuated when their probability is low.
- 3. Mislabeled very hard negative samples, with p>p\*, where p\* is defined as the point where  $\frac{\mathrm{d}}{\mathrm{d}p}\left(\frac{\mathrm{d}L}{\mathrm{d}z}\right)=0$ , which are suspected as mislabeled when the network computes a very large probability for a negative sample, it is possible that the sample was mislabeled, and its correct label should be positive. It has been shown by [11] that multi-label datasets are prone to mislabeling of negative samples, probably because the manual labeling task is difficult. When dealing with highly imbalanced datasets, even a small mislabeling rate of negative samples largely impact the training. Hence, rejection of mislabelled negative samples can be beneficial. The rejection must be done carefully, to allow the network to propagate gradients from actual misclassified negative examples.

In Table 1 we compare the properties and abilities of ASL to other losses, according to the gradient analysis.

We can see from Table 1 that only when we combine the two asymmetry mechanisms, focusing and probability margin, we can enjoy all the abilities and advantages which

	Hard Threshold	Soft Threshold	Discard Mislabeled	Continuous Gradients	
CE	-	-	-	+	
AF	-	+	-	+	
CE+PS	+	-	+	-	
ASL (AF+PS)	+	+	+	+	

Table 1: **Properties of various loss mechanisms**. CE = cross-entropy, AF = Asymmetric Focusing, PS = Probability Shifting.

are beneficial for imbalanced datasets: hard thresholding of very easy samples, non-linear attenuation of easy samples, rejection of mislabeled samples and continuous loss gradients.

### 2.6. Probability Analysis

In this section, we wish to provide further support to our claim that in multi-label datasets, using a symmetric loss such as cross entropy or focal loss is sub-optimal for learning positive samples' features. We do that by observing the average probabilities outputted by the network during the training. This allows us to evaluate the network's level of confidence for positive and negative samples. Low confidence suggests that features were not learned properly. We begin by defining  $p_t$  as:

$$p_t = \begin{cases} \bar{p} & \text{if } y = 1\\ 1 - \bar{p} & \text{otherwise} \end{cases}$$
 (8)

where  $\bar{p}$  denotes the average probability of the samples in a batch at each iteration. Denote by  $p_t^+$  and  $p_t^-$  the average probabilities of the positive and negative samples, respectively, and by  $\Delta p$  the probability gap:

$$\Delta p = p_t^+ - p_t^-. \tag{9}$$

A balanced training should demonstrate similar level of mean confidence for positive and negative samples, i.e.,  $\Delta p$  should be small throughout and at the end of the training. In Figure 4 we present the average probabilities  $p_t^+$  and  $p_t^-$  along the training, for three different loss functions: crossentropy, focal loss and ASL.

Figure 4 demonstrates the limitation of using symmetric losses for imbalanced datasets. When training with either cross-entropy loss or focal loss, we observe that  $p_t^-\gg p_t^+$  (at the end of the training,  $\Delta p=-0.23$  and  $\Delta p=-0.1$ , respectively). This implies that the optimization process gave too much weight to negative samples. Conversely, when training with ASL we can eliminate the gap, implying that the network has the ability to properly emphasize positive samples.

Notice that by lowering the decision threshold  $p_{th}$  at inference time (a sample will be declared as positive if

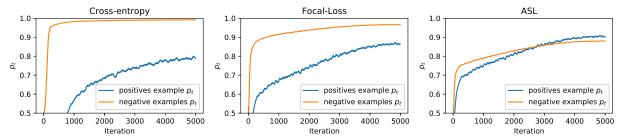


Figure 4: **Probability analysis.** The mean probability of positive and negative samples along the training with cross-entropy, focal loss and ASL, on MS-COCO. For focal loss we used  $\gamma = 2$ . For ASL we used  $\gamma_+ = 0$ ,  $\gamma_- = 2$ , m = 0.2.

 $p>p_{th}$ ), we can control the precision vs. recall tradeoff, and favor high true-positive rate over low false-negative rate. However, a large negative probability gap, as obtained by the symmetric losses, suggests that the network underemphasized gradients from positive samples and converged to a local minima, with sub-optimal performances. We will validate this claim in Section 3.

#### 2.7. Adaptive Asymmetry

Hyper-parameters of a loss function are usually adjusted via a manual tuning process. This process is often cumbersome and requires a level of expertise, since it is not straightforward to understand and predict each hyper-parameter's impact on the final score. Based on our probability analysis, we wish to offer a simple intuitive way of dynamically adjusting ASL's asymmetry levels, with a single interpretable control parameter.

In the last section we demonstrated that ASL enables to balance a network, and prevent a situation where negative samples have significantly larger  $p_t$  than positive samples  $(\Delta p < 0)$ . We now wish to go the other way around, and adjust  $\gamma_-$  dynamically throughout the training, to match a desired probability gap, denoted by  $\Delta p_{\rm target}$ . We can achieve this by a simple adaptation of  $\gamma_-$  after each batch, as described in Eq. 10.

$$\gamma_{-} \leftarrow \gamma_{-} + \lambda(\Delta p - \Delta p_{\text{target}})$$
 (10)

where  $\lambda$  is a dedicated step size. As we increase  $\Delta p_{\rm target}$ , Eq. 10 enables us to dynamically increase the asymmetry level throughout the training, forcing the optimization process to focus more on the positive samples' gradients. Notice that using similar logic to Eq. 10, we can also dynamically adjust the probability margin, or simultaneously adjust both asymmetry mechanisms. For simplicity, we chose to explore the case of adjusting only  $\gamma_-$  throughout the training, with  $\gamma_+=0$  and a small fixed probability margin.

Figure 9 in appendix A presents the values of  $\gamma_-$  and  $\Delta p$  throughout the training, for  $\Delta p_{\rm target}=0.1$ . After 10% of the training, the network converges successfully to the target probability gap, and to a stable value of  $\gamma_-$ . In the

next section we will analyze the mAP score and possible use-cases for this dynamic scheme.

## 3. Experimental Study

In this section, we will provide experimentations and comparisons to better understand the different losses, and demonstrate the improvement we gain from utilizing ASL, in comparison with other losses. We will also test our adaptive asymmetry mechanism, and compare it to a fixed hyperparameters scheme. For testing, we will use the well-known MS-COCO [22] dataset (see Section 4.1.1 for full dataset and training details).

**Focal Loss Vs Cross-Entropy:** In Figure 5 we present the mAP scores obtained for different values of focal loss  $\gamma$  ( $\gamma=0$  is cross-entropy). We can see from Figure 5 that

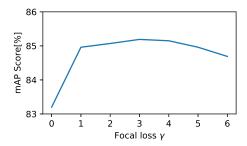


Figure 5: **mAP Vs. Focal Loss**  $\gamma$ **.** Comparing MS-COCO mAP score for different values of focal loss  $\gamma$ .

with cross-entropy loss, the mAP score is lower than the one obtained with focal loss (83.2% vs 85.1%). Top scores with focal loss are obtained for  $2 \le \gamma \le 4$ . With  $\gamma$  below that range, the loss does not provide enough down-weighting for easy negative samples. With  $\gamma$  above that range, there is too much down-weighting of the rare positive samples.

**Asymmetric Focusing:** In Figure 6 we test the asymmetric focusing mechanism: for two fixed values of  $\gamma_-$ , 2 and 4, we present the mAP score along the  $\gamma_+$  axis. Figure 6 demonstrates the effectiveness of asymmetrical focusing - as we decrease  $\gamma_+$  (hence increasing the level of asymmetry), the mAP score significantly improves.

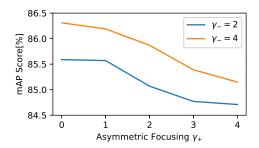


Figure 6: mAP Vs. Asymmetric Focusing  $\gamma_+$ . Comparing MS-COCO mAP score for different value of asymmetric focusing  $\gamma_+$ , for  $\gamma_-=2$  and  $\gamma_-=4$ .

Interestingly, we found that simply setting  $\gamma_+=0$  leads to the best results in our experiments. That may further support the importance of keeping the gradient magnitudes high for positive samples. Indeed, allowing  $\gamma_+>0$  may be useful for cases where there is also an abundance of easy positive samples. Note that we also tried training with  $\gamma_+<0$ , to extend the asymmetry further. However, these trials did not converge, therefore they are not presented in Figure 6.

**Asymmetric Probability Margin:** In Figure 7 we apply our second asymmetry mechanism, asymmetric probability margin, on top of cross-entropy loss ( $\gamma=0$ ) and two levels of (symmetric) focal loss,  $\gamma=2$  and  $\gamma=4$ . We

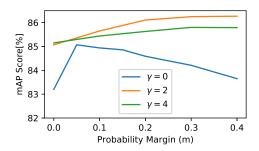


Figure 7: **mAP Vs.** Asymmetric Probability Margin. Comparing MS-COCO mAP score for different values of asymmetric probability margin, on top of a symmetric focal loss, with  $\gamma = 0, 2, 4$ 

can see from Figure 7 that both for cross-entropy and focal loss, introducing asymmetric probability margin improves the mAP score. For cross-entropy, the optimal probability margin is low, m=0.05, in agreement with our gradient analysis - cross-entropy with probability margin produces a non-smooth loss gradient, with less attenuation of easy samples. Hence, a small probability margin, which still enables hard threshold for very easy samples and rejection of mislabeled samples, is better. For focal loss, the optimal probability margin is significantly higher,  $0.3 \le m \le 0.4$ . This again can be explained by analyzing the loss gradi-

ents: since focal loss already has non-linear attenuation of easy samples, we need a larger probability margin to introduce meaningful asymmetry. We can also see that when introducing asymmetric probability margin, better scores are obtained for  $\gamma=2$  compared to  $\gamma=4$ , meaning that asymmetric probability margin works better on top of a modest amount of focal loss.

Combining Asymmetries: Until now we tested each ASL asymmetry separately. In Table 2 we compare the top mAP scores, achieved when combining the asymmetries together, to the top mAP scores obtained when applying each asymmetry alone. We can see from Table 2 that the best

Asymmetry Type	Top mAP Score [%]
Focusing	86.3
Probability Margin	86.3
Focusing + Probability Margin	86.6

Table 2: **Top COCO mAP scores for different ASL asymmetries.** Top focusing mAP obtained for  $\gamma_+=0, \gamma_-=3$ . Top margin mAP obtained for  $\gamma=2, m=0.3$ . Top combined mAP obtained for  $\gamma_+=0, \gamma_-=4, m=0.05$ .

results are obtained when combining the two components of asymmetry. This correlates with our analysis of the loss gradients in Figure 3, where we demonstrate how combining the two asymmetries enables discarding of very easy samples, nonlinear attenuation of easy samples and rejection of possibly mislabeled very hard negative samples, a result which is not possible when applying only one type of asymmetry.

**Adaptive Asymmetry:** We now examine the effectiveness of adjusting the ASL asymmetry levels dynamically, via the procedure proposed in Eq.10. In Table 3 we present the mAP score, and the final value of  $\gamma_-$ , obtained for various values of  $\Delta p_{\rm target}$ .

$\Delta p_{\mathrm{target}}$	$\gamma_{-}$ Final	mAP Score [%]
0	1.2	85.8
0.1	3.3	86.1
0.2	5.2	86.4
0.3	6.2	86.3

Table 3: **Adaptive Asymmetry**. mAP scores and  $\gamma_{-}$  obtained from adaptive asymmetry runs, for different  $\Delta p_{\rm target}$ , with  $\lambda=0.1$ .

We can see from Table 3 that even without any tuning, demanding the unbiased case  $\Delta p_{\rm target}=0$ , a significant improvement is achieved compared to focal loss (85.8% vs. 85.1%). Even better scores are obtained when using a higher probability gap,  $\Delta p_{\rm target}=0.2$ . Interestingly, extra focus on the rare positive samples ( $\Delta p_{\rm target}>0$ ) is better

than just demanding the unbiased case.

Notice that the top mAP scores obtained from the dynamic scheme are still lower by 0.2% compared to the best ASL score with a fixed  $\gamma_-$ . One possible reason for this (small) degradation is that the training process is highly impacted by the first epochs [14]. Tuning hyper-parameter dynamically may be sub-optimal at the beginning of the training, which decreases the overall performance. To compensate for the initial recovery iterations, dynamically-tuned  $\gamma_-$  tends to converge to higher values, but the overall score is still somewhat hindered. Due to this decline, we chose to use a fixed asymmetry scheme in section 4.

Still, the dynamic scheme can be appealing to a non-expert user, as it allows control of the asymmetry level via one simple interpretable hyper-parameter. In addition, we will explore in the future ways to expand this scheme for other useful applications, such as tuning  $\gamma_-$  adaptively per class, which can be impractical with a regular exhaustive search.

#### 4. Dataset Results

In this section, we will evaluate ASL on four popular multi-label classification datasets, and compare its results to known state-of-the-art techniques, and to commonly used loss functions in multi-label training. We will also test ASL's applicability to other computer vision tasks, such as single-label classification and object detection.

#### 4.1. Multi-Label Datasets

#### 4.1.1 MS-COCO

MS-COCO [22] is a widely used dataset to evaluate computer vision tasks such as object detection, semantic segmentation and image captioning, and has been adopted recently to evaluate multi-label image classification. For multi-label classification, it contains 122, 218 images with 80 different categories, where every image contains on average 2.9 labels, thus giving an average positive-negative ratio of:  $\frac{2.9}{80-2.9}=0.0376$ . The dataset is divided to a training set of 82,081 images and a validation set of 40,137 images. Following conventional settings for MS-COCO [32, 23], we report the following statistics: mean average precision (mAP), average per-class precision (CP), recall (CR), F1 (CF1) and the average overall precision (OP), recall (OR) and F1 (OF1), for the overall statistics and top-3 highest scores. Among these metrics, mAP, OF1, and CF1 are the main metrics, since they take into account both falsenegative and false-positive rates. In Table 4 we present results for the main metrics, for training with three different loss functions: ASL, focal loss and cross-entropy, and compare them to known state-of-the-art methods from the literature (Full training details and loss hyper-parameters are provided in appendix B). In Table 8 in appendix C we bring

results for all the metrices.

Method	mAP	CF1	OF1
CADM [5]	82.3	77.0	79.6
ML-GCN [6]	83.0	78.0	80.3
KSSNet [23]	83.7	77.2	81.5
MS-CMA [37]	83.8	78.4	81.0
MCAR [13]	83.8	78.0	80.3
CE (Ours)	83.2	77.3	81.0
Focal loss (Ours)	85.1	79.1	81.5
ASL (Ours)	86.6	81.4	81.8

Table 4: Comparison of ASL to other loss functions and to state-of-the-art models on MS-COCO. All metrics are in %. Results are reported for input resolution 448.

We can see from Table 4 that ASL provides better results than cross-entropy and focal loss on MS-COCO. ASL also significantly outperforms previous state-of-the-art methods, with mAP score 2.8% higher than the previous top method. Notice that our ASL-based solution does not increase inference time or training (and architecture) complexity, unlike solutions proposed in previous methods, which include intricate architecture modifications (attentional regions [13], GCNs [38]) and injecting external data (label embeddings [37, 5], teacher model [23]). Also notice that the mAP scores for MS-COCO are highly influenced by the input resolution. For a fair comparison, we report in Table 4 results for standard input resolution, 448. In Table 9 in appendix D we show that with higher input resolutions, our mAP score can be increased to 88.4%.

In Figure 8 we test the applicability of ASL for different backbones, by comparing different loss functions on three commonly used architectures: OFA-595 [2], Resnet101 [15] and TResNet-L [26]. We can see from Figure 8 that on all backbones, ASL outperforms focal loss and crossentropy, demonstrating its robustness to backbone selection.

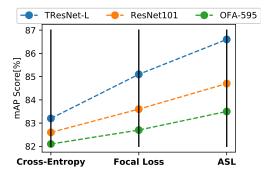


Figure 8: Testing different losses on various backbones.

#### 4.1.2 Pascal-VOC

Pascal Visual Object Classes Challenge (VOC 2007) [12] is another popular dataset for multi-label recognition. It

contains images from 20 object categories, with an average of 2.5 categories per image. Pascal-VOC is divided to a trainval set of 5,011 images and a test set of 4,952 images. Our training settings were identical to the ones used for MS-COCO. Notice that most previous works on Pascal-VOC used simple ImageNet pre-training, but some used additional data, like pre-training on MS-COCO or using NLP models like BERT. For a fair comparison, we present our results once with ImageNet pre-training, and once with additional pre-train data (MS-COCO) and compare them to the relevant works. Results appear in Table 5.

	mAP	mAP
Method	(ImageNet	(Extra
	Only Pretrain)	Pretrain Data)
RNN [33]	91.9	-
FeV+LV [35]	92.0	-
SSGRL [4]	93.4	95.0
ML-GCN [6]	94.0	-
BMML [20]	-	95.0
CE (Ours)	93.2	95.0
Focal loss (Ours)	93.8	95.4
ASL (Ours)	94.6	95.8

Table 5: Comparison of ASL to known state-of-the-art models on Pascal-VOC dataset. Metrics are in %.

We can see from Table 5 that ASL achieves new state-of-the-art results on Pascal-VOC, with and without additional pre-training. We also see that additional (MS-COCO) pre-training can significantly improve the mAP score, compared with standard ImageNet pre-training.

## **4.1.3 NUS-WIDE**

NUS-WIDE [7] dataset originally contained 269,648 images from Flicker, that have been manually annotated with 81 visual concepts. Since some urls have been deleted, we were able to download only 220,000 images, similar to [11, 31] (see appendix for more details about obtaining the dataset), and used the standard 70-30 train-test split [11, 31, 23]. Our training settings were identical to the ones used for MS-COCO. In Table 6 we compare ASL results with current state-of-the art models and different loss functions on NUS-WIDE.

tions on NUS-WIDE. We can see from Table 6 that ASL improves the known state-of-the-art result on NUS-WIDE by a large margin - 2.4% mAP. Other metrics also show improvement.

#### 4.1.4 Open Images

Open Images (v6) [19] is a large scale dataset, which consists of 9 million training images, 41,620 validation images and 125,436 test images. It is partially annotated with human labels and machine-generated labels.

Method	mAP	CF1	OF1
S-CLs [23]	60.1	58.7	73.7
MS-CMA [37]	61.4	60.5	73.8
SRN [40]	62.0	58.5	73.4
ICME [5]	62.8	60.7	74.1
CE (Ours)	63.1	61.7	74.6
Focal loss (Ours)	64.0	62.9	74.7
ASL (Ours)	65.2	63.6	75.0

Table 6: Comparison of ASL to known state-of-the-art models on NUS-WIDE dataset. All metrics are in %.

The scale of Open Images is much larger than previous multi-label datasets such as NUS-WIDE, Pascal-VOC and MS-COCO. Also, it contains a considerable amount of unannotated labels. That allows us to test ASL on extreme classification [39], and high mislabeleing scenarios. Full dataset and training details appear in the appendix F.

To the best of our knowledge, no results for other methods were published yet for v6 variant of Open Images. Hence, we compare ASL only to the other common loss functions in multi-label classification. Yet we hope that our result can serve as a benchmark for future comparisons. In addition to the standard (micro) mAP metric, we also choose to state the macro mAP score, since we believe it better represents the actual visual quality of the network. Results appear in Table 7.

Method	micro mAP[%]	macro mAP[%]
CE	84.8	92.0
Focal Loss	84.9	92.2
ASL	86.3	92.8

Table 7: Comparison of ASL to focal loss and crossentropy on Open Images V6 dataset.

We can see from Table 7 that ASL significantly outperforms regular focal loss and cross-entropy on Open Images, demonstrating that ASL is suitable for large datasets and extreme classification cases.

#### 4.2. Additional Computer Vision Tasks

In addition to multi-label classification, we wanted to test ASL on other relevant computer vision tasks. Since fine-grain single-label classification and object detection tasks usually contain a large portion of background or long-tail cases [1, 18], and are known to benefit from using focal loss, we chose to test ASL on these tasks. In sections G and H in the appendix we show that ASL outperform focal loss on relevant datasets for these additional tasks, demonstrating that ASL is not limited only to multi-label classification.

#### 5. Conclusion

In this paper, we present an asymmetric loss (ASL) for multi-label classification. ASL contains two complementary asymmetric mechanisms, which operate differently on positive and negative samples. By examining ASL derivatives, we gained a deeper understanding of the loss properties. Through network probability analysis, we demonstrate the effectiveness of ASL in balancing between negative and positive samples, and proposed an adaptive scheme that can dynamically adjusts the asymmetry levels throughout the training. Extensive experimental analysis shows that ASL outperforms common loss function and previous state-of-the-art approaches on popular multi-label classification benchmarks, including MS-COCO, Pascal-VOC, NUS-WIDE and Open Images.

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## **Appendices**

## A. Adaptive Asymmetry dynamics

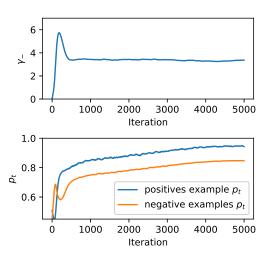


Figure 9: Adaptive Asymmetry Dynamics. Values of  $\gamma_{-}$  and  $\Delta p$  throughout the training, for  $\Delta p_{\text{target}} = 0.1$ .  $\gamma_{+}$  is set to 0, m is set to 0.05.

## **B.** Multi-Label General Training Details

Unless stated explicitly otherwise, for all multi-label datasets we used the following training procedure: As a backbone, we used TResNet-L, which is modern architecture, equivalent in run-time to ResNet101, with improved accuracy [26]. We trained the model for 25 epochs using Adam optimizer and 1-cycle policy [27], with maximal learning rate of 2e-4. For regularization, we used Cutout factor of 0.5 [10], True-weight-decay [24] of 1e-4 and gpu augmentations. We found that the common ImageNet statistics normalization [16, 8, 28] does not improve results, and instead used a simpler normalization - scaling all the RGB channels to be between 0 and 1. Following the experiments in section 3, for ASL we used  $\gamma_-=4$ ,  $\gamma_+=0$  and m=0.05, and for focal loss we used  $\gamma=2$ .

## C. Comparing MS-COCO On All Common Metrics

In Table 8 we compare ASL results, to known state-of-the-art methods, on all common metrics for MS-COCO dataset.

## D. MS-COCO mAP Scores for High-Resolution Inputs

The mAP score we report in Table 8 is for standard input resolution, 448, with TResNet-L as architecture. However,

using higher input resolutions with larger architectures is highly beneficial for the mAP score. Notice that the input resolution is not always mentioned in articles [23], or sometimes a larger-than-standard input resolution is used [36]. For completeness, in Table 9 we compare results with input resolution larger than 448. Notice that ResNet101 architecture has similar runtime to TResNet-L [26].

## E. Obtaining NUS-WIDE

Some of the original flicker links to NUS-WDIE are not longer available. We can find in previous works [11, 31, 23] many variants of NUS-WIDE dataset, and its hard to do a one-to-one comparison. We obtained our variant of NUS-WIDE from: https://drive.google.com/file/d/0B7IzDz-4yH HMFdiSI

This variant contains 218,942 images. We recommend using it for standardization and a completely fair comparison in future works.

#### F. Open Images Training Details

Due to missing links on flicker, we were able to download only 114,648 test images from Open Images dataset, which contain about 5,400 unique tagged classes. For dealing with the partial labeling methodology of Open Images dataset, we set all untagged labels as negative, with reduced weights. Due to the large the number of images, we trained our network for 30 epochs on input resolution of 224, and finetuned it for 5 epochs on input resolution of 448. Since the level of positive-negative imbalancing is significantly higher than MS-COCO, we increased the level of loss asymmetry: For ASL, we trained with  $\gamma = 7, \gamma_+ = 0$ .For Focal loss, we trained with  $\gamma = 4$ . Other training details are similar to the ones used for MS-COCO.

# G. Fine-Grain Single-Label Classification Results

For testing ASL on fine-grain single-label classification, we chose to work on the competitive Herbarium 2020 FGVC7 Challenge [18]. The goal of Herbarium 2020 is to identify vascular plant species from a large, long-tailed collection Herbarium specimens provided by the New York Botanical Garden (NYBG). The dataset contains over 1M images representing over 32,000 plant species. This is a dataset with a long tail; there are a minimum of 3 specimens per species, however, some species are represented by more than a hundred specimens. The metric chosen for the competition is macro F1 score. For Focal loss, we trained with  $\gamma=2$ . For ASL, we trained with  $\gamma=4$ ,  $\gamma_+=0$ . The metric chosen for the competition is macro F1 score. In Table 10 we bring results of ASL on Herbarium dataset, and compare it to regular focal loss. We can see from Table 10

Method		All			Top 3								
Method	mAP	CP	CR	CF1	OP	OR	OF1	CP	CR	CF1	OP	OR	OF1
CADM [5]	82.3	82.5	72.2	77.0	84.0	75.6	79.6	87.1	63.6	73.5	89.4	66.0	76.0
ML-GCN [6]	83.0	85.1	72.0	78.0	85.8	75.4	80.3	87.2	64.6	74.2	89.1	66.7	76.3
KSSNet [23]	83.7	84.6	73.2	77.2	87.8	76.2	81.5	-	-	-	-	-	-
MS-CMA [37]	83.8	82.9	74.4	78.4	84.4	77.9	81.0	86.7	64.9	74.3	90.9	67.2	77.2
MCAR [13]	83.8	85.0	72.1	78.0	88.0	73.9	80.3	88.1	65.5	<b>75.1</b>	91.0	66.3	76.7
ASL	86.6	87.2	76.4	81.4	88.2	79.2	81.8	91.8	63.4	75.1	92.9	66.4	77.4

Table 8: Comparison of ASL to known state-of-the-art models on MS-COCO dataset. All metrics are in %. Results are reported for input resolution 448.

Method	Architecture	Input Resolution	mAP	
ADD-GCN [13]	ResNet-101 GCN	512	85.2	
ASL	TResNet-L	448	86.5	
ASL	TResNet-L	640	88.0	
ASL	TResNet-XL	640	88.4	

Table 9: Comparison of MS-COCO mAP scores for high-resolution inputs. All metrics are in %

Method	macro F1 [%]
Focal Loss	76.1
ASL	<b>77.6</b>

Table 10: **Comparison of ASL to focal loss on Herbarium dataset**. Macro-F1 is the competition official metrics. All results are on an unseen private-set.

that ASL outperforms focal loss on this fine-grain singlelabel classification dataset by a large margin. Note that Herbarium 2020 was a CVPR-Kaggle classification competition. Our ASL test-set score would achieve the 3rd place in the competition, among 153 teams.

## **H.** Object Detection Results

For testing ASL on object detection, we used the MS-COCO [22] dataset (object detection task), which contains a training set of 118k images, and an evaluation set of 5k images. For training, we used the popular mm-detection [3] package, with the enhancements discussed in ATSS [38] and FCOS [29] as the object detection method. We trained a TResNet-M [26] model with SGD optimizer for 70 epochs, with momentum of 0.9 , weight decay of 0.0001 and batch size of 48. We used learning rate warm up, initial learning rate of 0.01 and 10x reduction at epochs 40, 60. For ASL we used  $\gamma_+ = 1, \gamma_- = 2$ . For focal loss we used the common value,  $\gamma_- = 2$  [21]. Note that unlike multi-label and fine-grain single-label classification datasets, for object de-

tection  $\gamma_+=0$  was not the optimal solution. The reason for this might be the need to balance the contribution from the 3 losses used in object detection (classification, bounding box and centerness). We should further investigate this issue in the future.

Our object detection method, FCOS [29], uses 3 different types of losses: classification (focal loss), bounding box (IoU loss) and centerness (plain cross-entropy). The only component which is effected by the large presence of background samples is the classification loss. Hence, for testing we replaced only the classification focal loss with ASL.

In Table 11 we compare the mAP score obtained from ASL training to the score obtained with standard focal loss. We can see from Table 11 that ASL outscores regular focal loss, yielding an 0.4% improvement to the mAP score.

Method	mAP [%]
Focal Loss	44.0
ASL	44.4

Table 11: Comparison of ASL to focal loss on MS-COCO detection dataset.