Mish: A Self Regularized Non-Monotonic Neural Activation Function

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Abstract

The concept of non-linearity in a Neural Network is introduced by an activation function which serves an integral role in the training and performance evaluation of the network. Over the years of theoretical research, many activation functions have been proposed, however, only a few are widely used in mostly all applications which include ReLU (Rectified Linear Unit), TanH (Tan Hyperbolic), Sigmoid, Leaky ReLU and Swish. In this work, a novel activation function, Mish is proposed which can be defined as:

\[ f(x) = x \cdot \tanh(\text{softplus}(x)) = x \cdot \tanh(\ln(1 + e^x)) \]

The experiments show that Mish tends to work better than both ReLU and Swish along with other standard activation functions in many deep networks across challenging datasets. For instance, in Squeeze Excite Net-18 for CIFAR 100 classification, the network with Mish had an increase in Top-1 test accuracy by 0.494% and 1.671% as compared to the same network with Swish and ReLU respectively. The similarity to Swish along with providing a boost in performance and its simplicity in implementation makes it easier for researchers and developers to use Mish in their Neural Network Models.

1. Introduction

The mathematical computation in every deep neural network model includes a linear transformation followed by an activation function. This activation function is the key towards introducing non-linearity in the network. Activation functions play a crucial role in the performance of every deep network. Currently, in the deep learning community, two activation functions have been predominately being used as the standard for all applications. These two are: Rectified Linear Unit (ReLU) [1,2,3] which can be defined by \( f(x) = \max(0,x) \) and Swish [4,5] which can be defined as: \( f(x) = x \cdot \text{sigmoid}(x) \).

ReLU has been used as the standard/ default activation function in mostly all applications courtesy to its simple implementation and consistent performance as compared to other activation functions. Over the years, many activation functions have been proposed to replace ReLU which includes Square Non-Linearity (SQNL) [6], Exponential Linear Unit (ELU), Parametric Rectified Linear Unit (PReLU) [7] along with many others. However, the simplicity and efficiency of ReLU remained unchallenged throughout, until Swish Activation Function was released which showcased strong and improved results on many challenging benchmarks. Unlike ReLU, Swish is a smooth non-monotonic activation function and similar to ReLU, it is bounded below and unbounded above. Swish demonstrated significant improvements in top-1 test accuracy across many deep networks in challenging datasets like ImageNet.

In this paper, Mish, a novel neural activation function is introduced. Similar to Swish, Mish is a smooth and non-monotonic activation function which can be defined as:

\[ f(x) = x \cdot \tanh(\text{softplus}(x)) = x \cdot \tanh(\ln(1 + e^x)) \]

Throughout the extensive testing and experimentation conducted Mish demonstrated better results than both Swish and ReLU. For example, during classification of CIFAR-100 dataset using a Squeeze Excite -18 Network [8] with Mish resulted in an increase in Top-1 test accuracy by 0.494% and 1.671% as compared to the same network with Swish and ReLU respectively. Mish provides near consistent improvement in accuracy over Swish and ReLU as seen in case of CIFAR-100 classification using a MobileNet v2 [9] where the network with Mish had an increase in Top-1 test accuracy by 1.385% over Swish and 0.8702% over ReLU.

2. Mish

Mish is a novel smooth and non-monotonic neural activation function which can be defined as:

\[ f(x) = x \cdot \tanh(\zeta(x)) \]

where, \( \zeta(x) = \ln(1 + e^x) \) is the softplus activation [10] function. The graph of Mish is shown in Figure 1.

![Mish Activation Function](image)
Like both Swish and ReLU, Mish is bounded below and unbounded above with a range \([-0.31, \infty)\). The derivative of Mish shown in Figure 2 is defined as:

\[
f'(x) = \frac{e^x \omega}{\delta^2}
\]

where \(\omega = 4(x + 1) + 4e^{2x} + e^3 + e^4(4x + 6)\) and \(\delta = 2e^{2x} + e^{2x} + 2\). The minimum of Mish is observed to be at \(x \approx -1.1924\) with a magnitude of \(\approx -0.30884\). Mish takes inspiration from Swish by using a property called Self Gating, where the scalar input is provided to the gate. The property of Self-gating is advantageous for replacing activation functions like ReLU (point-wise functions) which take in a single scalar input without requiring to change the network parameters.

Mish can be easily implemented using any standard deep learning framework by defining a custom activation layer. In Tensorflow [11], the function definition of Mish can be written as \(x \times \text{tf.math.tanh(tf.softplus(x))}\) while in Torch [12] it is \(x \times \text{torch.tanh(F.softplus(x))}\). For improved results over ReLU, it is advised to use a slightly lower learning rate for Mish.

### 2.1. Properties of Mish

Although it’s difficult to explain the reason why one activation function performs better than another due to many other training factors, the properties of Mish like being unbounded above, bounded below, smooth and non-monotonic, all play a significant role in the improvement of results. Figure 3 shows the different commonly used activation functions along with the graph of Mish activation for comparison.

| Table 1. Properties Summary of Mish |
|-------------------------------------|
| **Order of Continuity** | \(C^\infty\) |
| **Monotonic** | No |
| **Monotonic Derivative** | No |
| **Saturated** | No |
| **Approximates Identity Near Origin** | Yes |
Being unbounded above is a desirable property for any activation function since it avoids saturation which generally causes training to drastically slow down due to near-zero gradients [13]. Being bounded below is also advantageous since it results in strong regularization effects. The non-monotonic property of Mish causes small negative inputs to be preserved as negative outputs as shown in Figure 4, which improves expressivity and gradient flow. The order of continuity being infinite for Mish is also a benefit over ReLU since ReLU has an order of continuity as 0 which means it’s not continuously differentiable causing some undesired problems in gradient-based optimization.

Mish being a smooth function also plays an important role in explaining the improvement in results as it helps with effective optimization and generalization. The output landscape of 5 layer randomly initialized neural network was compared for ReLU, Swish, and Mish. The observation as shown in Figure 5, clearly depicts the sharp transition between the scalar magnitudes for the co-ordinates of ReLU as compared to Swish and Mish. Smoother transition results in smoother loss functions which are easier to optimize and hence the network generalizes better which partially explains why Mish outperforms ReLU. However, in this regards, Mish and Swish are extremely similar in their corresponding output landscapes.

3. Comparison of variation in hyperparameters

To observe how increasing the number of layers in a network while maintaining other parameters constant affect the test accuracy, fully connected networks of varying depths on MNIST, with each layer having 500 neurons were trained. Residual Connections [17] were not used because they enable the training of arbitrarily deep networks. BatchNorm [15] was used to lessen the dependence on initialization along with a dropout [16] of 25%. The network is optimized using SGD [17] on a batch size of 128, and for fair comparison, the same learning rates for each activation function was maintained. In the experiments, all 3 activations maintained nearly the same...
test accuracy for 15 layered Network. Increasing the number of layers from 15 gradually resulted in a sharp decrease in test accuracy for Swish and ReLU, however, Mish outperformed them both in large networks where optimization becomes difficult as shown in Figure 6.

The consistency of Mish providing better test top-1 accuracy as compared to Swish and ReLU was also observed by increasing Batch Size for ResNet v2-20 on CIFAR-10 for 50 epochs while keeping all other network parameters to be constant for fair comparison as demonstrated in Figure 7.

4. Experiments

In total, at the time of this paper publication, Mish activation function has been validated on more than 70 benchmarks in problems ranging from Image Classification, Image Segmentation and Generative Models against a total of 15 activation functions on challenging datasets including CIFAR-10, CIFAR-100, CalTech-256 and ASL to name a few. Table 2 provides a summary of these results. However, it is to be noted that being more computationally expensive, Mish usually takes more time per epoch as compared to Swish and ReLU.

Comparison is done based on the high priority metric, for image classification the Top-1 Accuracy while for Generative Networks and Image Segmentation the Loss Metric. Therefore, for the latter, “Mish > Baseline” is indicative of better loss and vice versa.

Table 2 is a concrete and conclusive proof of the robustness and efficiency of Mish activation function as compared to other baseline activation functions especially Swish and ReLU, which, as observed is outperformed 50 times across 73 benchmark experiments. These benchmarks were performed using a variety of models including DenseNet [18], Inception v3 [19], Xception Net [20] amongst many others.

Table 2. Benchmark Summary of Mish

| Activation Function | Mish > Baseline | Mish < Baseline |
|---------------------|-----------------|-----------------|
| ReLU                | 50              | 23              |
| Swish               | 50              | 23              |
| ELU                 | 4               | 1               |
| Aria-2              | 1               | 0               |
| Bent’s Identity     | 1               | 0               |
| Hard Sigmoid        | 1               | 0               |
| Leaky ReLU          | 2               | 1               |
| PReLU               | 2               | 0               |
| SELU                | 4               | 0               |
| Sigmoid             | 2               | 0               |
| Softplus            | 1               | 0               |
| Softsign            | 2               | 0               |
| TanH                | 2               | 0               |
| SQNL                | 1               | 0               |
| Thresholded ReLU    | 1               | 0               |

4.1. CIFAR

Table 3. CIFAR-10 Results (Test Top-1 Accuracy)

| Model                  | Mish     | Swish    | ReLU     |
|------------------------|----------|----------|----------|
| ResNet v2-20           | 92.02%   | 91.61%   | 91.71%   |
| WRN 10-2               | 86.83%   | 86.56%   | 84.56%   |
| SimpleNet              | 91.70%   | 91.44%   | 91.16%   |
| Xception Net           | 88.73%   | 88.56%   | 88.38%   |
| Capsule Net            | 83.15%   | 82.48%   | 82.19%   |
| Inception ResNet v2    | 85.21%   | 84.96%   | 82.22%   |
| DenseNet-121           | 91.27%   | 90.92%   | 91.09%   |
| MobileNet v2           | 86.25%   | 86.08%   | 86.05%   |
| Shuffle Net v1         | 87.31%   | 86.95%   | 87.04%   |
| Inception v3           | 91.19%   | 91.17%   | 90.84%   |
| Efficient Net B0       | 80.73%   | 79.37%   | 79.31%   |

Table 4. CIFAR-100 Results (Test Top-1 Accuracy)

| Model                  | Mish     | Swish    | ReLU     |
|------------------------|----------|----------|----------|
| ResNet v2-110          | 74.41%   | 74.13%   | 73%      |
| WRN 22-10              | 72.32%   | 71.89%   | 72.2%    |
| WRN 40-4               | 69.52%   | 69.59%   | 69.35%   |
| DenseNet -121          | 66.31%   | 65.91%   | 65.50%   |
| DenseNet -169          | 65.38%   | 65.69%   | 64.99%   |
| ResNext-50             | 67.58%   | 66.72%   | 67.52%   |
| MobileNet v1           | 50.09%   | 49.95%   | 49.20%   |
| SE Net-18              | 64.38%   | 63.89%   | 62.71%   |
| Shuffle Net v2         | 59.35%   | 58.91%   | 58.56%   |
| Squeeze Net            | 63.07%   | 62.11%   | 60.92%   |
Table 3 and 4 provide Top-1 Test accuracy stats of various models trained on Mish, Swish and ReLU. For reduction of reading complexity, fraction of the experiment results out of all the benchmarks conducted is shown. As seen in both the tables, Mish consistently outperforms both ReLU and Swish with higher Top-1 testing accuracy while keeping every other parameter of the model to be constant.

Figure 8 shows the Training Graph of ResNet v1-32 on CIFAR 10 using Mish, Swish and ReLU. As shown in the figure, Mish has a higher epoch time as compared to ReLU and Swish which can be commented as one of its drawbacks in comparison to other commonly used baseline activation functions.

5. Conclusion

Mish is a novel neural activation function defined by the formula: $f(x) = x \cdot \tanh(softplus(x))$. Being a non-monotonic, self-gated/regularized, smooth activation function; it demonstrates its capability and robustness in improving the results of a Neural Network task as compared to Swish and ReLU. The experiments concluded had models specifically synthesized with parameters favorable for ReLU, where in-place of ReLU, Swish and

All conducted and to-be-conducted benchmarks are available on the GitHub repository of this paper.
Mish were added correspondingly to obtain the results. This is a proof of its efficiency and suggests even improved performances with networks initialized with hyperparameters for Mish. Although, there is a certain trade-off of higher epoch time as observed in Mish, the improved accuracy and with the availability of higher compute it becomes a robust choice to replace Swish and ReLU in a model with Mish activation function.

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