ProbAct: A probabilistic Activation Function

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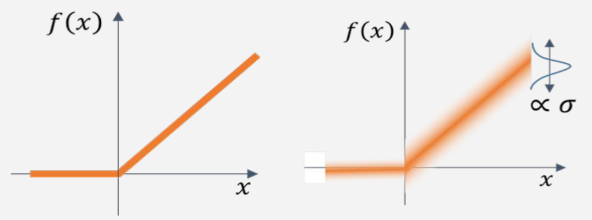
Abstract

ProbAct is a novel stochastic activation function composed of a mean and variance with the output value sampled from the formed distribution. Stochastic perturbation induced through ProbAct is shown to act as a viable generalization technique for feature augmentation. We compare ProbAct with well-known activation functions on classification tasks on Images and Text dataset and achieved performance improvements of +2-3%.

ProbAct: A Stochastic Activation Function



- Every layer of a neural network computes its output y for the given input x:

$$y = f(W^T x)$$

where *w* is the weight vector of the layer and f(·) is an activation function, such as ProbAct.

- ProbAct is defined as:

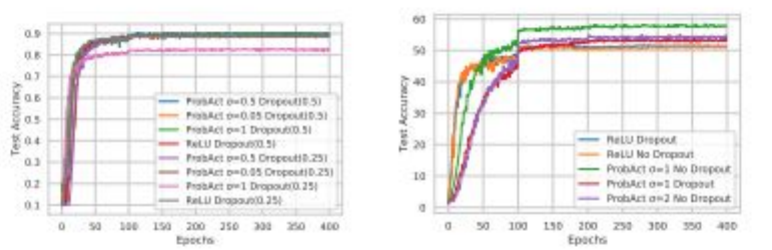
$$f(a) = \mu(a) + \sigma\epsilon$$

where *a* is the input to the activation function, μ(a) is a static or learnable mean, σ defines the range of stochastic perturbation (can be static or learnable) and ϵ is a random value sampled from a normal distribution N(0,1).

Experiments

- We evaluate ProbAct on the following image classification and sentiment analysis datasets :
  - CIFAR-10, CIFAR-100, and STL-10
  - Large Movie Review
- We compare ProbAct to the following activation functions and methods:
  - ReLU[1], Sigmoid, TanH, Leaky ReLU[2], PReLU[3], ELU[4], SELU[5], and Swish[6].
  - Bayesian VGG with Variational Inference[7]
- We used a 16 layer VGG for Image Classification and two-layered CNN for text classification task.
- No regularization, pre-training or data augmentation techniques were used.
- STL images were resized to 32 by 32.

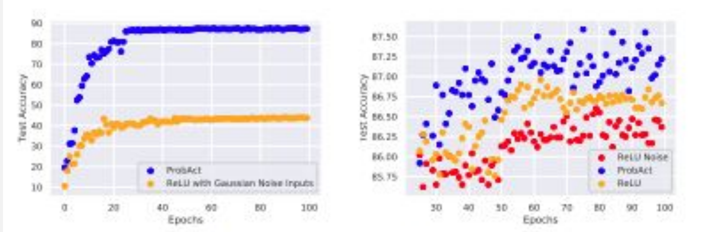
Accuracy Comparison between ReLU and ProbAct



(*a*) Test Acc CIFAR10 (*b*) Test Acc CIFAR100

Results and Discussion

Activation function	CIFAR-10	CIFAR-100	STL-10	IMDB	Train time (sec)	Test time (milli-sec)
Sigmoid	10.00	1.00	10.00	85.92	1.07	1.03
Tanh	10.00	1.00	10.00	85.88	1.08	1.03
ReLU	87.27	52.94	60.80	85.85	**1.00**	**1.00**
Leaky ReLU	86.49	49.44	59.16	85.47	1.04	1.08
PReLU	86.35	46.30	60.01	85.95	1.16	**1.00**
ELU	87.65	56.60	64.11	86.51	1.16	1.04
SELU	86.65	51.52	60.71	85.71	1.19	1.05
Swish	86.55	54.01	63.50	86.14	1.20	1.13
Bayesian VGG VI[1]	86.22	48.27	57.22	-	-	-
ProbAct						
Mean						
Element-wise μ	85.80	48.50	54.17	83.86	1.29	1.35
Sigma						
Fixed ($\sigma = 0.5$)	88.50	56.85	62.30	**87.31**	1.09	1.25
Fixed ($\sigma = 1.0$)	88.87	**58.45**	62.50	87.00	1.10	1.27
One Trainable σ	87.40	53.87	63.07	86.35	1.23	1.30
EW Trainable σ						
Unbound	86.40	54.10	61.70	86.64	1.25	1.31
Bound	**88.92**	55.83	**64.17**	85.86	1.26	1.33



(*c*) Noisy Input (*d*) Noisy Activation

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