Секция «Дискретная математика и математическая кибернетика»

Applying Lateral Inhibition in Data Enhancing of Deep Learning

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Due to the high complexity of deep learning models, the neural networks often overfit some unrelated features, such as the background or the high-frequency characteristics of images [1]. Inspired by the "Lateral Inhibition"[2] mechanism in the biological nervous system, we introduce the lateral inhibition algorithm in deep learning. This algorithm can significantly reduce the model's dependence on irrelevant information to improve the model's interpretability and robustness.

In the nervous system, highly activated nerve cells inhibit the activation of their own peripheral nerve cells, which can increase the contrast between strong and weak signals. We apply this mechanism to identify neurons that are important for the current task, so as to filter out the noise in the activation.

We use the Convolutional Neural Networks and apply our algorithm after each layer. The algorithm can be described as:

a) I=Input tensor, q=Quantile, σ=Sigma, k=Kernel size, r=Enhanced ratio.

b) Run network with input I, then in backpropagation process compute Importance of Neuron (IoN)-the differential between expected Loss L and every neuron outputs:

$$IoN_{i,j}^{n} = \frac{\partial L}{\partial x_{i,j}^{n}}$$

c) Compute IoM - Importance of Minicolumns(IoM) [3]:

$$IoM_{i,j,k} = Norm(IoN_{i,j,k}^{1}, IoN_{i,j,k}^{2}, ..., IoN_{i,j,k}^{C}),$$

$$i \in [1, N], j \in [1, H], k \in [1, W]$$

d) Construct discrete filter based on Laplacian of Gaussian operator LOG by given parameters σ and k and apply this filter on the IoM on the batch size dimension:

$$IoM_{i,H,W} = LOG(IoM_{i,H,W}), \quad i \in [1, N]$$

e) Use linear interpolation to scale all the IoM obtained from the previous step to the size H and W, then for every image in IoM, Calculate threshold value Q_i based on given parameter quantile q:

$$Q_i = Threshold(IoM_i, q), \quad i \in [1, N]$$

f) Create a zero-one(i.e zero is inhibited, one is activate) mask tensor of the same dimension as IoM by the following rules:

$$mask_{i,j,k} = \mathbb{I}\{IoM_{i,j,k} > 0\}$$

g) Select $r\%$ samples from the input tensor, then apply Gaussian blur for those inhibited areas (i.e where $mask = 0$) in these samples to obtain enhanced tensor $\tilde{I}$.

h) **Return** $\tilde{I}$

Figure 1 is the original image while Figure 2 is the enhanced image after applying lateral inhibition. Tabel 1 shows our significant improvment in ImageNet dataset.

Input	Test accuracy
Original Image	73.5%
Enhanced Image	77.9%

Таблица 1. Test on background fuzzy Imagenet dataset.

References

1) Xiao K, Engstrom L, Ilyas A, et al. Noise or signal: The role of image backgrounds in object recognition[J]. arXiv preprint arXiv:2006.09994, 2020.

2) Müller N G, Mollenhauer M, Rösler A, et al. The attentional field has a Mexican hat distribution[J]. Vision research, 2005, 45(9): 1129-1137.

3) Casanova M F, Buxhoeveden D, Gomez J. Disruption in the inhibitory architecture of the cell minicolumn: implications for autisim[J]. The Neuroscientist, 2003, 9(6): 496-507.

Illustrations

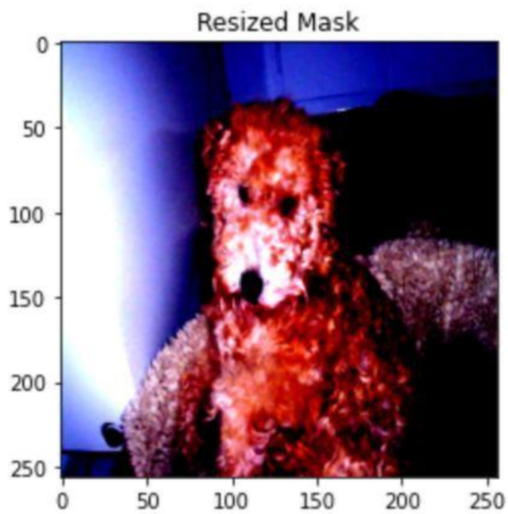

Рис. 1. Original Image

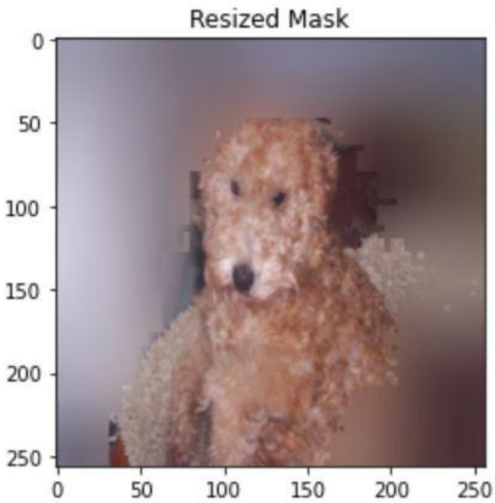

Рис. 2. Enhanced Image