interactive_video_retrieval/presentation/Paper Presentation Interactive Video Retrieval.pdf
https://github.com/lineojcd/interactive_video_retrieval/blob/master/presentation/Paper%20Presentation%20Interactive%20Video%20Retrieval.pdf

## Local Response Normalization

- **No need to input normalization with ReLUs.**
- **But still the following local normalization scheme helps generalization.**

$$b^i_{x,y} = a^i_{x,y} / \left( k + \alpha \sum_{j=\max(0,i-n/2)}^{\min(N-1,i+n/2)} (a^j_{x,y})^2 \right)^\beta$$

Response-normalized activity

Activity of a neuron computed by applying kernel I at position (x,y) and then applying the ReLU nonlinearity

- **Response normalization reduces top-1 and top-5 error rates by 1.4% and 1.2% , respectively.**

### 3.3 Local Response Normalization

ReLUs have the desirable property that they do not require input normalization to prevent them from saturating. If at least some training examples produce a positive input to a ReLU, learning will happen in that neuron. However, we still find that the following local normalization scheme aids generalization. Denoting by $a^i_{x,y}$ the activity of a neuron computed by applying kernel $i$ at position $(x, y)$ and then applying the ReLU nonlinearity, the response-normalized activity $b^i_{x,y}$ is given by the expression

$$b^i_{x,y} = a^i_{x,y} / \left( k + \alpha \sum_{j=\max(0,i-n/2)}^{\min(N-1,i+n/2)} (a^j_{x,y})^2 \right)^\beta$$

where the sum runs over $n$ "adjacent" kernel maps at the same spatial position, and $N$ is the total number of kernels in the layer. The ordering of the kernel maps is of course arbitrary and determined before training begins. This sort of response normalization implements a form of lateral inhibition inspired by the type found in real neurons, creating competition for big activities amongst neuron outputs computed using different kernels. The constants $k, n, \alpha$, and $\beta$ are hyper-parameters whose values are determined using a validation set; we used $k = 2$, $n = 5$, $\alpha = 10^{-4}$, and $\beta = 0.75$. We applied this normalization after applying the ReLU nonlinearity in certain layers (see Section 3.5).

Q： local contrast normalization

可能是 上式 a - mean 就是local contrast

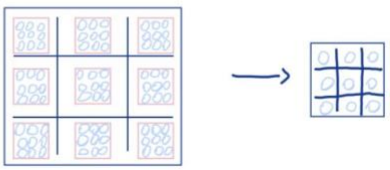
### 3.4 Overlapping Pooling

Pooling layers in CNNs summarize the outputs of neighboring groups of neurons in the same kernel map. Traditionally, the neighborhoods summarized by adjacent pooling units do not overlap (e.g., [17, 11, 4]). To be more precise, a pooling layer can be thought of as consisting of a grid of pooling units spaced $s$ pixels apart, each summarizing a neighborhood of size $z \times z$ centered at the location of the pooling unit. If we set $s = z$, we obtain traditional local pooling as commonly employed in CNNs. If we set $s < z$, we obtain overlapping pooling. This is what we use throughout our network, with $s = 2$ and $z = 3$. This scheme reduces the top-1 and top-5 error rates by 0.4% and 0.3%, respectively, as compared with the non-overlapping scheme $s = 2, z = 2$, which produces output of equivalent dimensions. We generally observe during training that models with overlapping pooling find it slightly more difficult to overfit.

## Overlapping Pooling

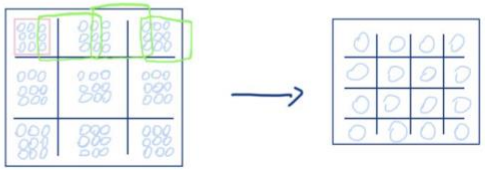
- **Traditional pooling (s = z)**

Non - Overlapping Pooling



- **s < z: overlapping pooling**
  - *In paper, s = 2, z = 3*

Overlapping - Pooling



### 3.5 Overall Architecture

Now we are ready to describe the overall architecture of our CNN. As depicted in Figure 2, the net contains eight layers with weights; the first five are convolutional and the remaining three are fully-connected. The output of the last fully-connected layer is fed to a 1000-way softmax which produces a distribution over the 1000 class labels. Our network maximizes the multinomial logistic regression objective, which is equivalent to maximizing the average across training cases of the log-probability of the correct label under the prediction distribution.

## Reducing Overfitting

- **Softmax**

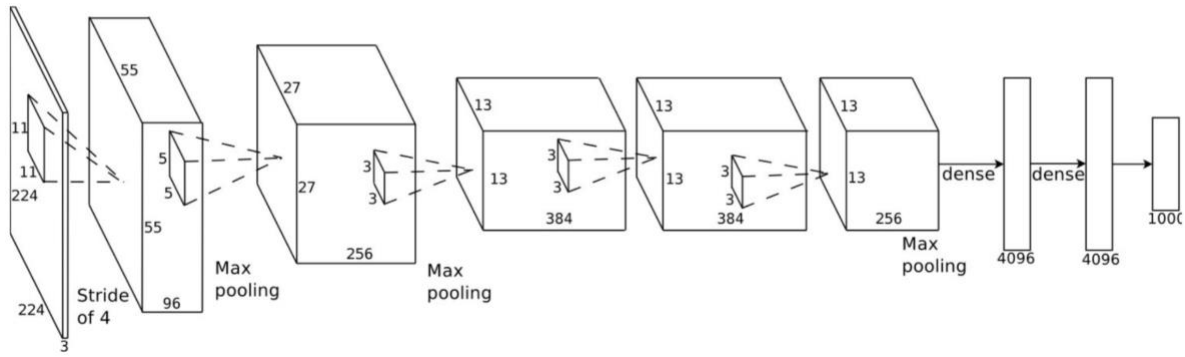
$$L = \frac{1}{N}\sum_i -\log\left(\frac{e^{f_{y_j}}}{\sum_j e^{f_j}}\right) + \lambda\sum_k\sum_l W_{k,l}^2$$

$j = 1...1000$

$P(y_i \mid x_i; W)$ Likelihood

The kernels of the second, fourth, and fifth convolutional layers are connected only to those kernel maps in the previous layer which reside on the same GPU (see Figure 2). The kernels of the third convolutional layer are connected to all kernel maps in the second layer. The neurons in the fully-connected layers are connected to all neurons in the previous layer. Response-normalization layers follow the first and second convolutional layers. Max-pooling layers, of the kind described in Section 3.4, follow both response-normalization layers as well as the fifth convolutional layer. The ReLU non-linearity is applied to the output of every convolutional and fully-connected layer.

### Architecture




The kernels of the second, fourth, and fifth convolutional layers are connected only to those kernel maps in the previous layer which reside on the same GPU (see Figure 2). The kernels of the third convolutional layer are connected to all kernel maps in the second layer. The neurons in the fully-connected layers are connected to all neurons in the previous layer. Response-normalization layers follow the first and second convolutional layers. Max-pooling layers, of the kind described in Section 3.4, follow both response-normalization layers as well as the fifth convolutional layer. The ReLU non-linearity is applied to the output of every convolutional and fully-connected layer.

WWYQ: 怎么计算卷积之后的output size?

floor( (224 - 11)/4 ) + 1 = 55

you can use this formula `[(W-K+2P)/S]+1`.

- W is the input volume - in your case 128
- K is the Kernel size - in your case 5
- P is the padding - in your case 0 i believe
- S is the stride - which you have not provided.