#### Learning and Vision Group, NUS, ILSVRC 2014

# NIN, Good! (您好)

(Network in Network)

Jian DONG, Min LIN, Yunchao WEI, Qiang CHEN\*, Wei, XIA, Hanjiang LAI, Shuicheng YAN

eleyans@nus.edu.sg
National University of Singapore
\* IBM Research Australia



**Episode-1: Network in Network, ILSVRC-2013** 

# "Network in Network" (NIN)

NIN: CNN with non-linear filters, yet without fully-connected layers

Convolutional Layer

Fully Connected Layer

CNN

Linear convolution

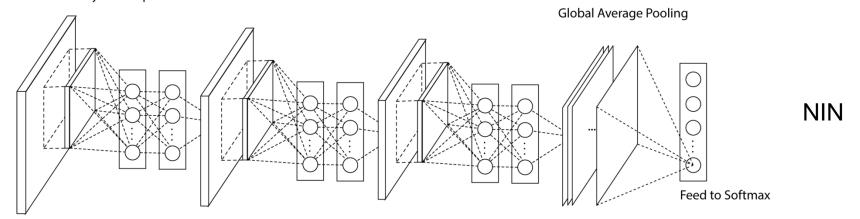
MLP convolution



# "Network in Network" (NIN)

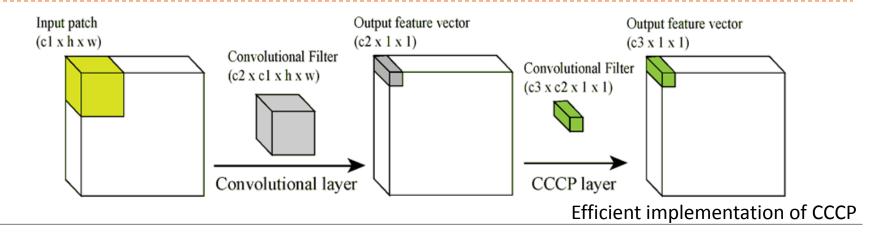
#### NIN: CNN with non-linear filters, yet without fully-connected layers

Multilayer Perceptron Convolution



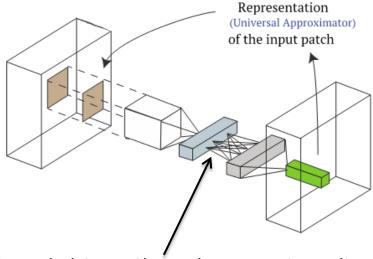


#### Better Local Abstraction ≈ Cascaded 1x1 Convolution



Local patch is projected to its value in a feature map using a small network

$$y_i = \phi(w_i^T y_{i-1} + b_i)$$
$$y_0 = x$$



Cascaded Cross Channel Parametric Pooling (CCCP)



# **Global Average Pooling**

Fully Connected Layers

Global Average Pooling
feature maps

output nodes

fully connected layers

output nodes

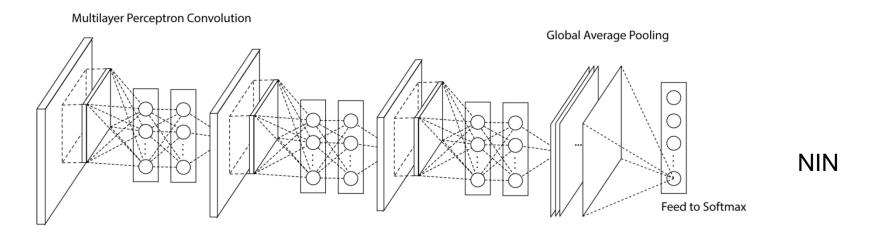
fully connected layers

Explicitly confidence map of each category

#### Save a large portion of parameters



### "Network in Network" (NIN) - Summary



Better local abstraction, less global overfitting, and much less parameters

	Cifar-10 Cifar-100	
Previous Best performance (Maxout) [1]	11.68%	38.57%
Our method	10.41%	36.30%

With less parameter #

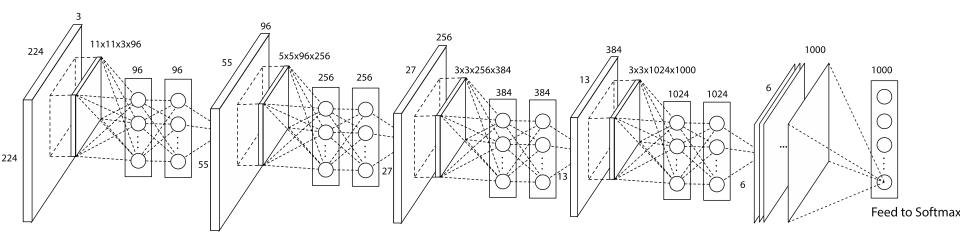


Episode-2: Network in Network, ILSVRC-2014

**ILSVRC-2014: Classification + Detection** 

### NIN for ImageNet Object Classification

A simple 4 layer NIN + Global Average Pooling:



	Parameter Number	Performance	Time to train (GTX Titan)
AlexNet	60 Million (230 Megabytes)	40.7% (Top 1)	8 days
NIN	7.5 Million (29 Megabytes)	39.2% (Top 1)	4 days





### NIN for ImageNet Object Classification

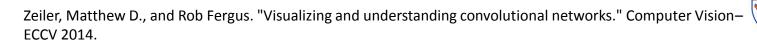
To avoid hyper-parameter tuning, we put cccp layer directly on convolution

layers of ZFNet (Network in ZFNet)

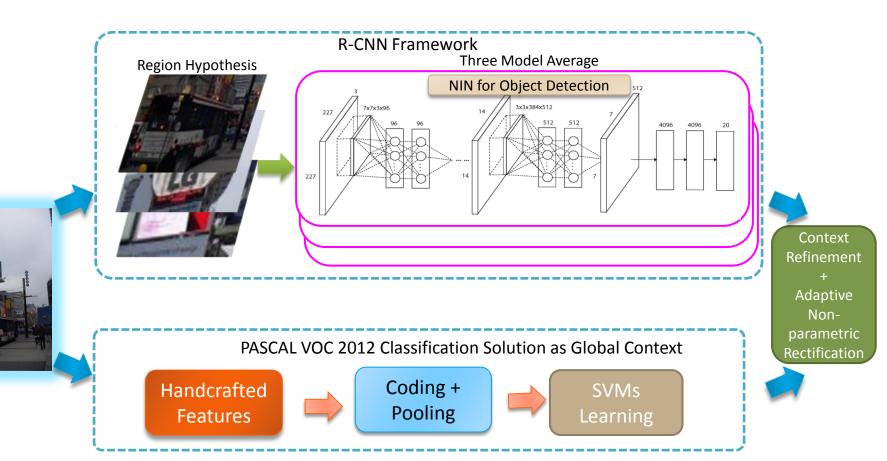
layer	details
Conv1	Stride = 2, kernel = 7x7, channel_out = 96
Conv2	Stride = 2, kernel = 5x5, channel_out = 256
Conv3	Stride = 1, kernel = 3x3, channel_out = 512
Conv4	Stride = 1, kernel = 3x3, channel_out = 1024
Conv5	Stride = 1 Vichan Not deep enough!
Fc1	Output Output
Fc2	Output = 4096
Fc3	Output = 1000

layer	details
Conv1	Stride = 2, kernel = 7x7, channel_out = 96
Cccp1	Output = 96
Conv2	Stride = 2, kernel = 5x5, channel_out = 256
Cccp2	Output = 256
Conv3	Stride = 1, kernel = 3x3, channel_out = 512
Ссср3	Output = 256
Conv4	Stride = 1, kernel = 3x3, channel_out = 1024
Cccp4	Output = 512
Ссср5	Output = 384
Conv5	Stride = 1, kernel = 3x3, channel_out = 512
Ссср6	Output = 256
Fc1	Output = 4096
Fc2	Output = 4096
Fc3	Output = 1000

(10.91% for 1 model, 9.79% for 3 models) with 256xN training and 3 view test

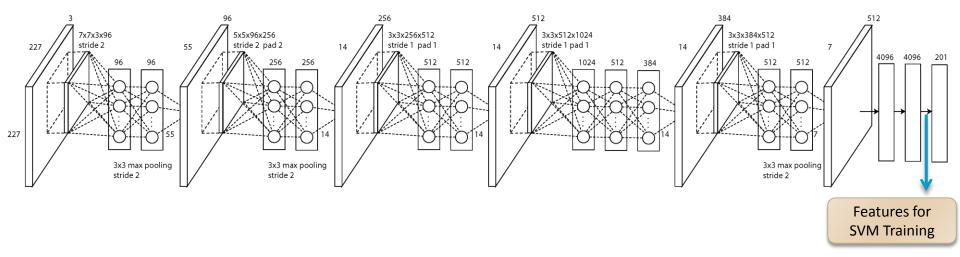


# NIN for ImageNet Object Detection





### NIN for ImageNet Object Detection



- Pre-training the NIN on ILSVRC14 detection train set
- Fine-tuning on train (partial) + validation set
  - Discard the parameters of the last layer



#### NIN for ImageNet Object Detection

▶ Results on validation set (0.5:0.5 of val set for validation and testing)

Submission	Method	MAP
NIN	the baseline result by using NIN as feature extractor for RCNN	35.61%
3 NINs	Using concatenated features from multiple NIN as feature extractor for RCNN	36.52% (↑0.91%)
3 NINs + ctx	adaptive non-parametric rectification of outputs from both object detectors and global context	37.49% (↑0.97%)

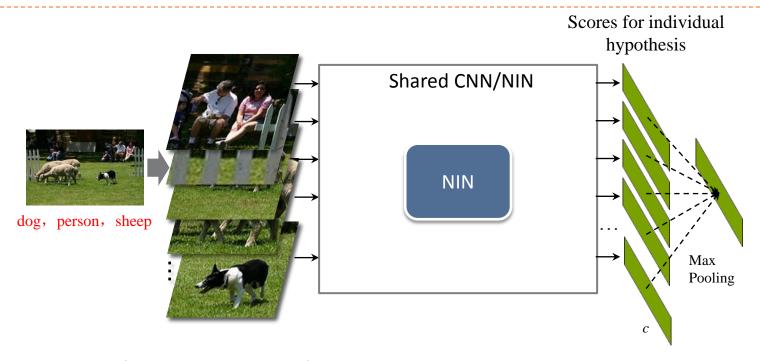
#### Results on test set

3 NINs + ctx	adaptive non-parametric rectification of outputs from both 37.212%
	object detectors and global context



**PASCAL-VOC-2012: Multi-label Classification** 

#### NIN for Pascal VOC Multi-label Classification



- ▶ HCP = Hypotheses + CNN + Pooling
- No ground-truth bounding box is required for training
- ▶ The proposed infrastructure is **robust** to the **noisy and/or redundant hypotheses**
- No explicit hypothesis label is required for training
- ▶ The shared CNN can be well **pre-trained** with a large-scale single-label image dataset



#### Classification State-of-the-arts on VOC 2012

Category	NUS-PSL[1]	PRE-1000C[2]	PRE-1512[2]	Chatfield <i>et al.</i> [3]	HCP	HCP+NUS-PSL
plane	97.3	93.5	94.6	96.8	98.4	99.5
bicycle	84.2	78.4	82.9	82.5	89.5	93.7
bird	80.8	87.7	88.2	91.5	96.2	96.8
boat	85.3	80.9	84.1	88.1	91.7	94.0
bottle	60.8	57.3	60.3	62.1	72.5	77.7
bus	89.9	85.0	89.0	88.3	91.1	95.3
car	86.8	81.6	84.4	81.9	87.2	92.4
cat	89.3	89.4	90.7	94.8	97.1	98.2
chair	75.4	66.9	72.1	70.3	73.0	86.1
cow	77.8	73.8	86.8	80.2	89.5	91.3
table	75.1	62.0	69.0	76.2	75.1	83.5
dog	83.0	89.5	92.1	92.9	96.3	97.3
horse	87.5	83.2	93.4	90.3	93.0	96.8
motor	90.1	87.6	88.6	89.3	90.5	96.3
person	95.0	95.8	96.1	95.2	94.8	95.8
plant	57.8	61.4	64.3	57.4	66.5	72.2
sheep	79.2	79.0	86.6	83.6	90.3	91.5
sofa	73.4	54.3	62.3	66.4	65.8	81.1
train	94.5	88.0	91.1	93.5	95.6	97.6
tv	80.7	78.3	79.8	81.9	82.0	90.0
MAP	82.2	78.7	82.8	83.2	86.8	91.4

<sup>[1]</sup> S. Yan, J. Dong, Q. Chen, Z. Song, Y. Pan, W. Xia, H. Zhongyang, Y. Hua, and S. Shen. Generalized hierarchical matching for subcategory aware object classification. In Visual Recognition Challange workshop, ECCV, 2012.

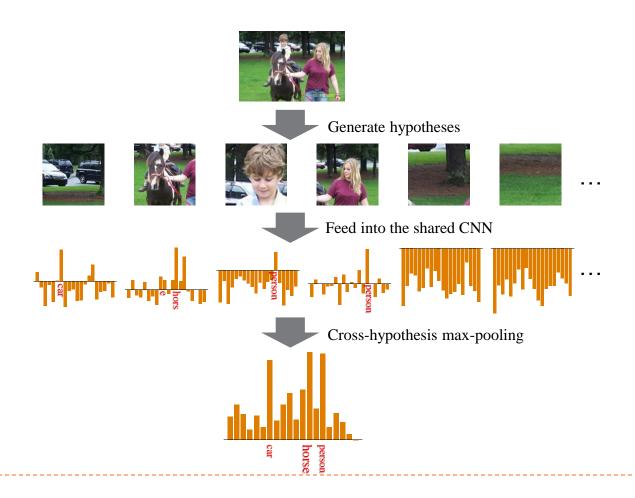
<sup>[3]</sup> K. Chatfield, K. Simonyan, A. Vedaldi, A. Zisserman. Return of the Devil in the Details: Delving Deep into Convolutional Nets, BMVC, 2014



<sup>[2]</sup> M. Oquab, L. Bottou, I. Laptev, and J. Sivic. Learning and transferring mid-level image representations using convolutional neural networks. CVPR, 2014.

#### NIN for Pascal VOC Multi-label Classification

Online demo with 1~1.5s per image





#### **Further Work**

What's next?

Definitely: "Deeper NIN"



#### **Great Appreciations to the Supports**





Microsoft® **Research** 溦软亚洲研究院







