

THE UNIVERSITY OF TENNESSEE KNOXVILLE

AICIP RESEARCH

ECE 599/692 – Deep Learning

Lecture 6 – CNN: The Variants

Hairong Qi, Gonzalez Family Professor
 Electrical Engineering and Computer Science
 University of Tennessee, Knoxville
<http://www.eecs.utk.edu/faculty/qi>
 Email: hqi@utk.edu

AICIP RESEARCH

Outline

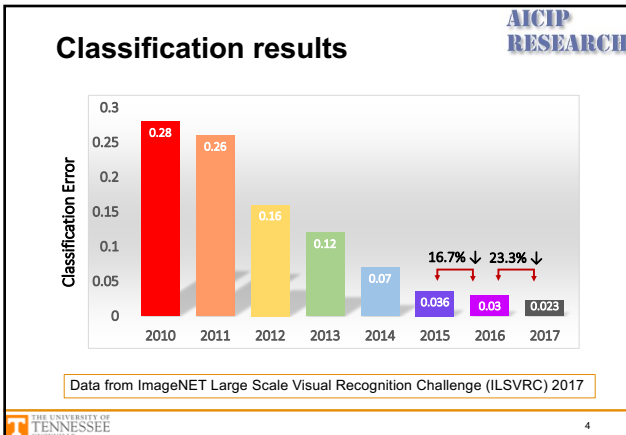
- Lecture 3: Core ideas of CNN
 - Receptive field
 - Pooling
 - Shared weight
 - Derivation of BP in CNN
- Lecture 4: Practical issues
 - The learning slowdown problem
 - Quadratic cost function
 - Cross-entropy + sigmoid
 - Log-likelihood + softmax
 - Overfitting and regularization
 - L2 vs. L1 normalization
 - Dropout
 - Artificially expanding the training set
 - Weight initialization
 - How to choose hyper-parameters
 - Learning rate, early stopping, learning schedule, regularization parameter, mini-batch size, Grid search
 - Others
 - Momentum-based GD
- Lecture 5: The representative power of NN
- Lecture 6: Variants of CNN
 - From LeNet to AlexNet to GoogleNet to VGG to ResNet
- Lecture 7: Implementation
- Lecture 8: Applications of CNN

AICIP RESEARCH

Participation in ILSVRC over the years

Year	Number of Entries
2010	35
2011	15
2012	29
2013	81
2014	123
2015	157
2016	172
2017	115

Data from ImageNET Large Scale Visual Recognition Challenge (ILSVRC) 2017



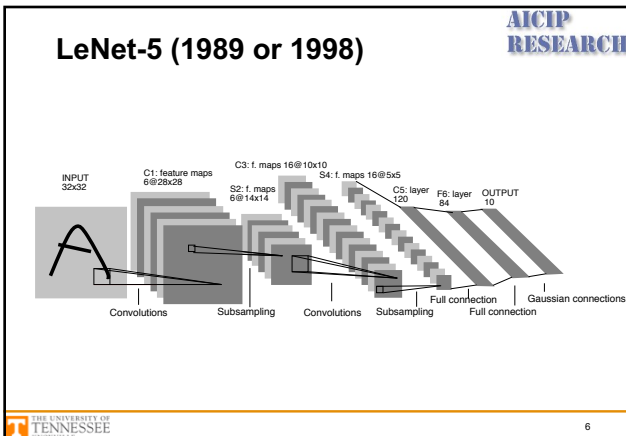
ImageNet Large Scale Visual Recognition Challenge (ILSVRC)

Year	Top-5 Error	Model
2010 winner	28.2%	Fast descriptor coding
2011 winner	25.7%	Compressed Fisher vectors
2012 winner	15.3%	AlexNet (8, 60M)
2013 winner	14.8%	ZFNet
2014 winner	6.67%	GoogLeNet (22, 4M)
2014 runner-up		VGGNet (16, 140M)
2015 winner	3.57%	ResNet (152)
2016 winner	3%	Ensembled approach - CUIImage
2017 winner	2.3%	SENet () - Momenta

Nov. 2017, Google AutoML outperform all human-constructed models, NASNet

Human expert: 5.1%

<https://www.independent.co.uk/life-style/gadgets-and-tech/news/google-child-ai-bot-nasnet-automl-machine-learning-artificial-intelligence-a8093201.html>



AlexNet (2012)

AICIP
RESEARCH

THE UNIVERSITY OF
TENNESSEE
7

AlexNet – Cont'

- Improvements
 - Bigger network
 - 8 layers (5 conv + 3 fc)
 - Layer 1: Conv+norm+relu+max-pooling
 - Layer 2: Conv+norm+relu+max-pooling
 - Layer 3: Conv+relu
 - Layer 4: Conv+relu
 - Layer 5: Conv+norm+relu
 - ...
 - ReLU vs. Sigmoid or tanh(x) $\sigma(z) = \frac{1}{1 + \exp(-z)}$
 - Training on multiple GPUs
 - Local response normalization $\sigma(z) = \tanh(z)$
 - Overlapping pooling
- Reduce overfitting
 - Data augmentation
 - Translation and horizontal mirror
 - Adding principal components from PCA
 - Dropout

THE UNIVERSITY OF
TENNESSEE
8

GoogLeNet (2014)

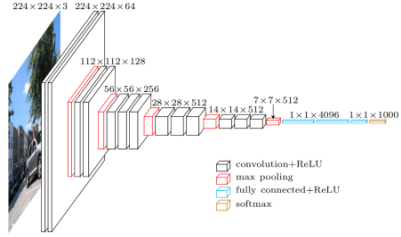
AICIP
RESEARCH

- Inception-v4
- Moving from fully connected to sparsely connected
- Finding optimal local construction and repeat spatially
- 22 layers

THE UNIVERSITY OF
TENNESSEE
9

VGGNet

- The extreme homogeneity in architectural design



ResNet

- Residual connection

