Paper Presentation

Insights for incremental learning

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Overview

1. Previous approach: Xiao, T., Zhang, J., Yang, K., Peng, Y., Zhang, Z. *Error-Driven Incremental Learning in Deep Convolutional Neural Network for Large-Scale Image Classification*. MM, 2014.
2. Insight for adjusting order of training points: Bengio, Y., Louradour, J., Collobert, R., Weston, J. *Curriculum Learning*, ICML 2009
3. Insight for designing loss function: Yi Sun, Yuheng Chen, Xiaogang Wang, Xiaoou Tang, *Deep Learning Face Representation by Joint Identification-Verification*, NIPS 2014

Previous approach

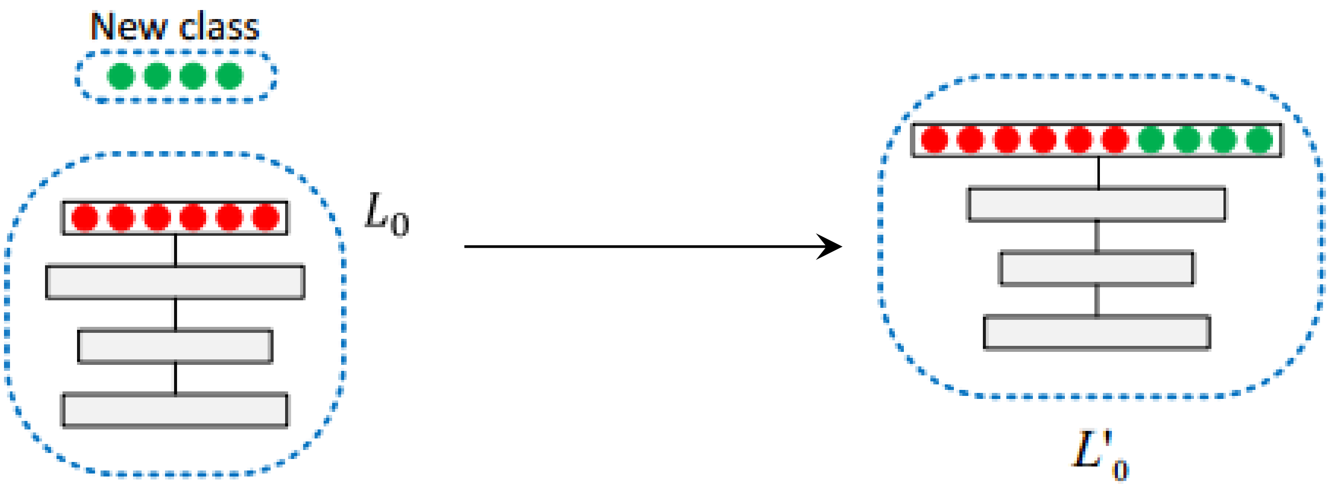
- Xiao, T., Zhang, J., Yang, K., Peng, Y., Zhang, Z. Error-Driven Incremental Learning in Deep Convolutional Neural Network for Large-Scale Image Classification. MM, 2014.

- What is incremental learning for CNNs?

- We have A CNN trained for old classes
- A new class coming in with training data
- Goal: Grow CNN incrementally. Comparing with training all classes from scratch, we want to 1. speed up training procedure; 2. Improve accuracy on new class; 3. Keep performances on old classes

Previous approach

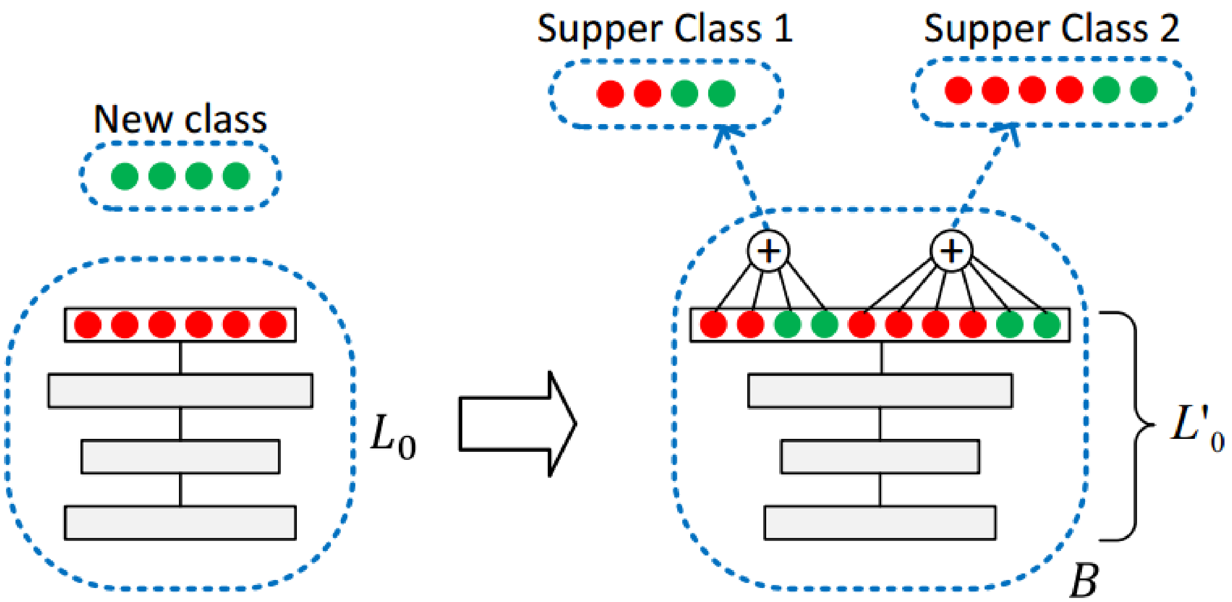
- Approach 1: one-level expansion



- Flat expansion: add new classes nodes in last layer
- Copy weights of L0 to L0'
- Randomly initialize weights between new classes nodes and the second last layer
- Use training data of new class to train L0'

Previous approach

- Approach 2: two-level expansion



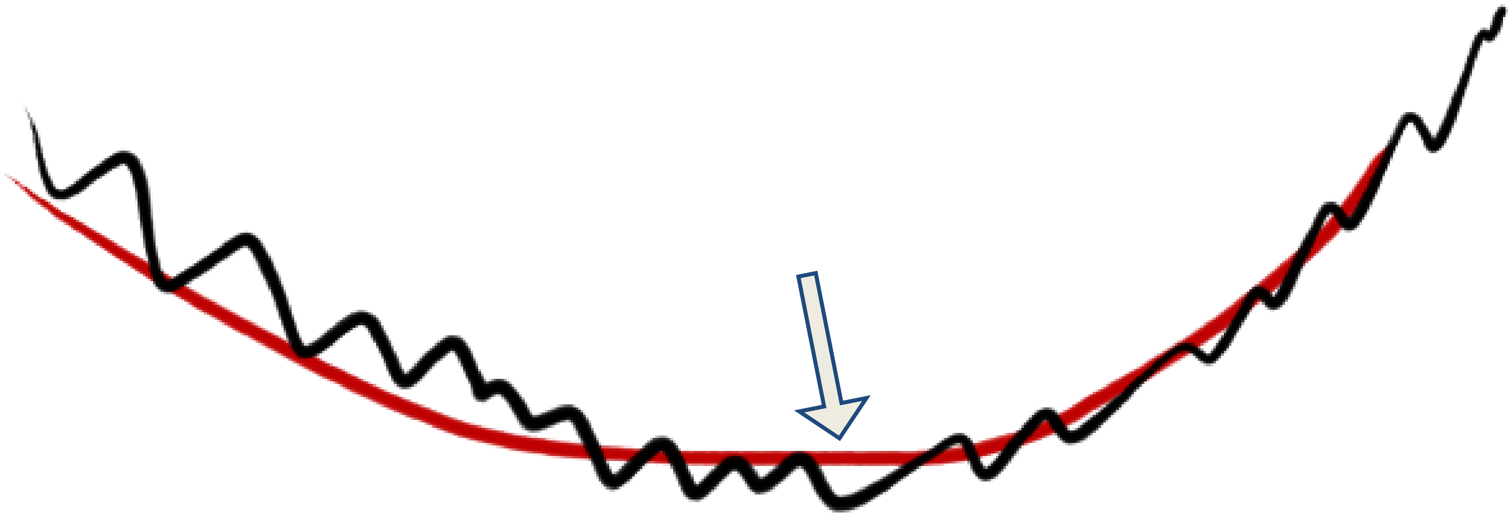
- Do one-level expansion first to obtain L0’
- Partition old and new classes into several superclasses
- Do one-level expansion for each superclass, just in last layer only include old and new nodes in this superclass
- Training: train each networks separately
- Testing: decide superclass first and then its fine-label

Insight for adjusting order of training points

- How to leverage similarity of old class and new class?
- Bengio, Y., Louradour, J., Collobert, R., Weston, J. Curriculum Learning, ICML 2009.
- Motivation: Humans learn much better when the examples are not randomly presented but organized in a order which first illustrates easy concepts, and gradually more complex ones.
- Basic idea: construct training points easier to learn - starting from data that is easier to learning, and ending with the target training data distribution

Curriculum Learning

- Learning deep architectures
  - Non-convex optimization problem
  - Many local minima
  - Target dataset - black curve
  - Easy training dataset - red curve, more smooth
  - Reach better local minima

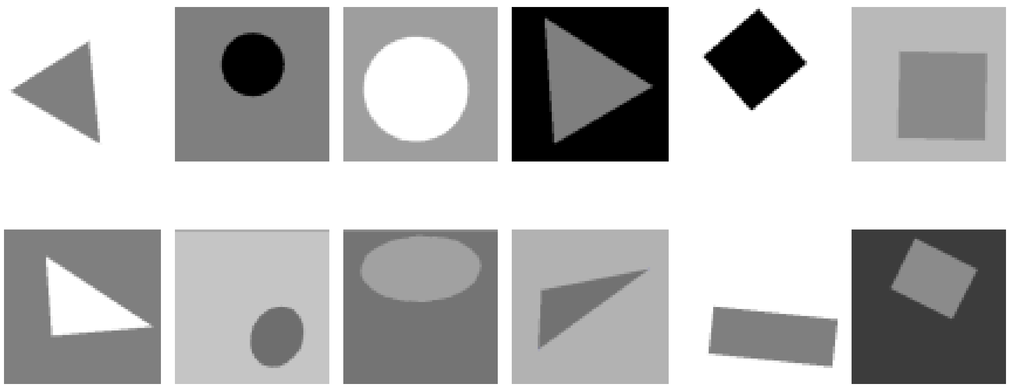


Curriculum Learning

- Experiments on shape recognition: The task is to classify geometrical shapes into 3 classes (rectangle, ellipse, triangle)

Basic

Target

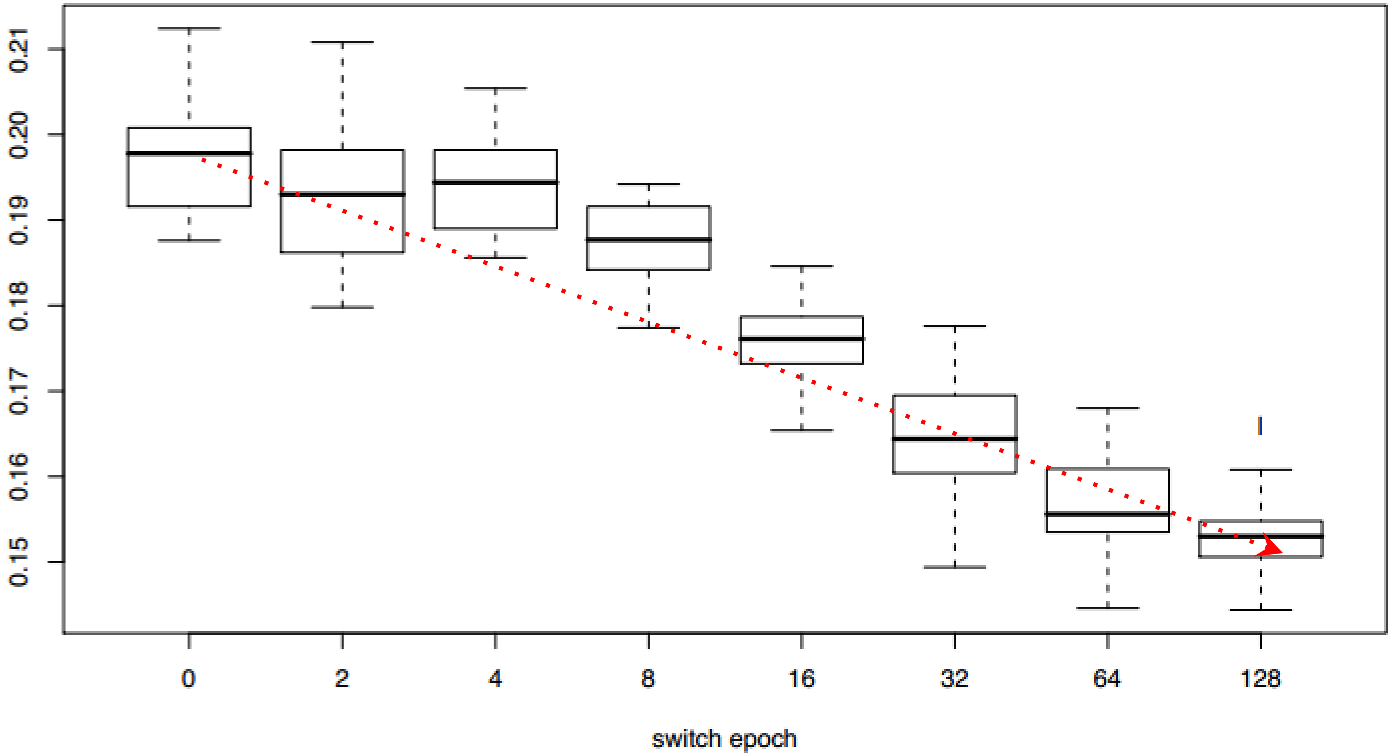


- 3-hidden layers deep net
- Use two stage curriculum:

Easy	Easy	Easy	Target	Target	Target

Curriculum Learning

- Results:



- Vertical axis: error rate
- Horizontal axis: switch epoch (#epochs training on easy)
- Each box corresponds to 20 random initializations
- As switch epoch increasing, the final accuracy improves
- Imply that curriculum learning helps deep nets to reach better local minima

Insight for adjusting order of training points

- How to use curriculum to leverage similarity of old class and new class to help incremental learning?

- Model the similarity between new class and old similar classes as one part of the easiness

N: #training points in each epoch

m: the number of training epochs

S_i: the similarity score vector. The old class A is the most similar class of new class B. When inputing data of B, O_i is the predicted score at node of A. In coarse network, set $S_i = O_i$; in fine network, set $S_i = 1 - O_i$.

D_i: the distance to feature mean $D_i = \left\|F_i - \overline{F}\right\|$

R_i: integer, with maximum value R. Indicate the times of training point i existed in these m epochs.

$$\min \sum_{i=1}^{N} \underbrace{(S_i + \lambda \cdot D_i)}_{\text{constant}} \times R_i$$

$$\text{s.t.} \sum_{i=1}^{N} R_i = m \cdot N, R_i \in Z^+, 1 \leq R_i \leq R$$

Insight for designing loss function

- Yi Sun, Yuheng Chen, Xiaogang Wang, Xiaoou Tang, Deep Learning Face Representation by Joint Identification -Verification, NIPS 2014

- Identification - Enlarge difference between different classes

Person 1	Person 2

- Verification - Decrease difference among same classes

Person 1	Person 1

Insight for designing loss function

- Yi Sun, Yuheng Chen, Xiaogang Wang, Xiaoou Tang, Deep Learning Face Representation by Joint Identification -Verification, NIPS 2014

- Identification loss - maximize difference between training data of different classes, basically using softmax loss

- Verification loss - minimize difference of extracted features at second last layer among training data of same classes

Insight for designing loss function

- In incremental learning, when training coarse network and fine networks, also use

  Identification loss + λ * Verification loss

- Identification loss - maximize difference between training data of different classes, basically using softmax loss

  → This is more important when training coarse network, set λ a bit smaller

- Verification loss - minimize difference of extracted features at second last layer among training data of same classes

  → This is more important when training fine network, set λ a bit larger

Thank you!