

lec 11

Image classification

Image Classification Challenges

- ① View Point Variation
- ② Interclass
- ③ Fine grained Categories
- ④ Background clutter
- ⑤ illumination
- ⑥ Deformation
- ⑦ occlusion

Applications

- ① object detection
- ② disease diagnosis
- ③ Image Captioning
- ④ playing Games (ex: Go)
- ⑤ Activity analysis

Image classification Based on Data driven approach

- ① Collect dataset of imgs, labels
- ② use Machine learning to train classifier
- ③ Evaluate Classifier to new images

Dataset

- ① MNIST → handwritten numbers → 10 Classes → 28X28
- ② CIFAR → 100 class → 32X32 → 20 Superclass
- ③ ImageNet → 1000 class → top 5 accuracy algo
- ④ MIT places → 365 Classes → 256 X 256

Conventional ML Classifier

(Classification over level of

- ① k-nearest neighbour (kNN)

Features)

↓

⇒ Not pixel level

train: Memorize all data labels

test: Predict label of most similar training image

uses

distance metric to Compare imgs

ex L_1 distance $\Rightarrow \sum p |p_1 - p_2|$

Decision boundary \rightarrow boundary between 2 classification regions

Can be noisy, affected by outliers

(kNN)

instead of Copying label from nearest neighbour
 \rightarrow take Majority vote from k closest points

use more neighbours \rightarrow smooth out region decision boundaries, help to reduce effect of outliers

when $(k > 1) \Rightarrow$ ties between classes
 \Rightarrow with right choice of distance metric, we can apply knn to any type of data

(L1) \rightarrow manhattan distance
 $|I_1^p - I_2^p|$ (Modulus)

(L2) \rightarrow Euclidean distance
(root) $\sqrt{\sum_p (I_1^p - I_2^p)^2}$

knn-hyper parameters

\rightarrow (k)
 \rightarrow distance metric

} very Problem Dependant

knn \rightarrow \otimes pixels but with ConvNet Features works well

Before \rightarrow linear score function $\rightarrow F = w \cdot x$
Now \rightarrow non linear (2-layer Neural net) $\rightarrow F = w_2 \max(0, w_1 \cdot x)$

Fully Connected Neural Network (1) Multi layer perceptron
→ layer 1 → layer 2 → layer 3
↓

ex Back Propagation model

Forward model

activation function \Rightarrow Sigmoid

- ① Forward Compute output
Backward Compute gradients

Deep Neural Network (generalized form from MNN)

- ② relu activation functions
hierarchical learning algo with many hidden layers
→ rectified linear unit

\Rightarrow if we build neural network without activation function

\Rightarrow linear classifier

Activation Function examples

- ① sigmoid ② tanh ③ ~~Relu~~ ④ leaky Relu ⑤ Maxout ⑥ ReLU
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Conventional Neural network (CNN)

- ① Fully Connected layers → output
- ② Activation Function → relu ($\max(0, wx)$)
- ③ Convolution layers
- ④ Pooling layers → reduce dimensions
- ⑤ Normalization

① Fully Connected layer
input array → stretch to vector → $X \times \text{weight}$ → dot product between row of (w) , input

② Convolutional layer (learn features) stack 2 Convolution → get another Convolution!

③ 32×32 Image ③ 5×5 Filter
Filter extend full depth ch input volume
⇒ Convolve filter with img
⇒ slide over img spatially to compute dot product

in first Convolutional layer → local image templates (simplest features)

Receptive Fields

Problem: large image need many layers
Solution: Downsample inside the network

③ Pooling layer ⇒ reduction of features
downsampling
max pool → maximum

kernel size stride pool function

Batch Normalize

Idea → Normalize outputs of layer so, they have Zero mean $= 0$, unit Variance $= 1$

↓
reduce interend Covariate shift

Batch Normalization
Fully Connected

$X: N \times D$

Convolutional
Batch normalization
 $(X: N \times C \times H \times W)$

Batch Normalization
usually inserted after Fully Connected layer
or Convolutional layer

before non linear

✓
much easy to train
high learning rate
Fast Convergence
robust to initialization

✗
- Not well understood
- Behave using training,