Convolutional Neural Networks for Visual Recognition (Spring 2019)

Lecture 1 | Introduction to CNN for Visual Recognition

Lecture 2 | Image Classification

- k-Nearest Neighbor

  > on images never used

  - L1 (Manhattan) distance: $d_1(I_1,I_2)=\sum_p{|I_1^p-I_2^p|}$
  - L2 (Euclidean) distance: $d_1(I_1,I_2)=\sqrt{\sum_p{(I_1^p-I_2^p)^2}}$

- Setting Hyperparameters

  1. Split data into train, validation, and test (only used once)
  2. Cross-Validation: Split data into folds

- Linear Classification

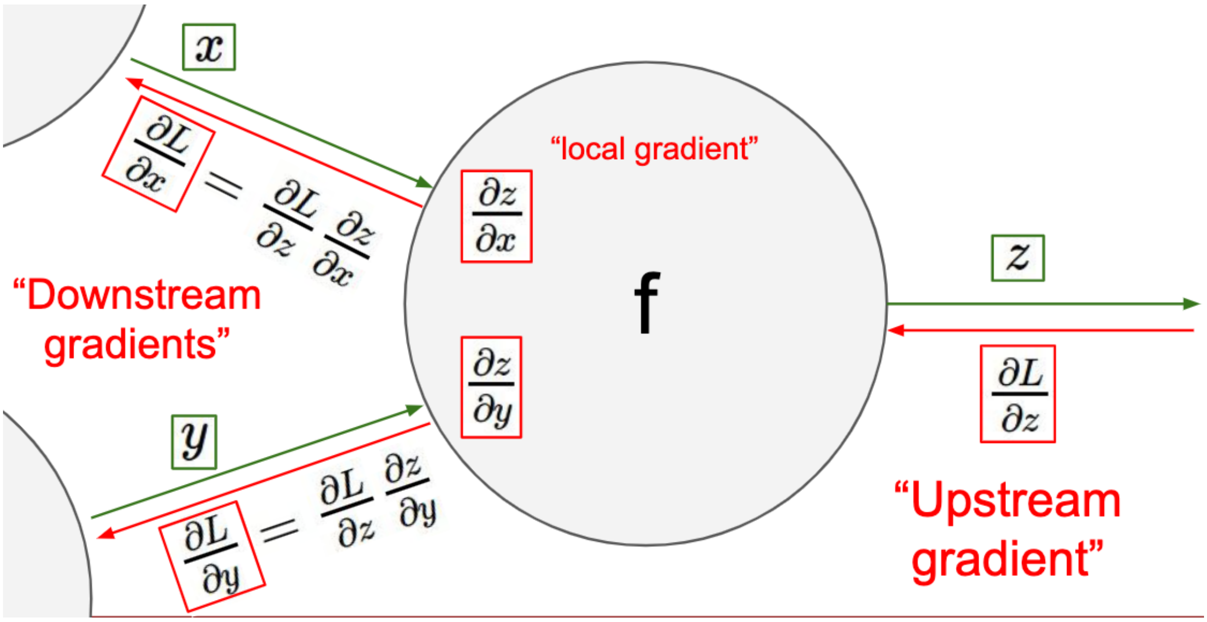
  - $s=f(x,W) = Wx + b$

Lecture 3 | Loss Functions and Optimization

- Multiclass SVM
  - $L_i=\sum_{j\not =y_i}\max(0,f(x_i;W)_j-f(x_i;W)_{y_i}+1)$
  - Loss Function: $$L=\frac{1}{N}\sum_{i=1}^NL_i=\frac{1}{N}\sum_{j\not =y_i}\max(0,f(x_i;W)_j-f(x_i;W)_{y_i}+1)$$
- Regularization
  - $$L(W)=\frac{1}{N}\sum_{i=1}^NL_i(f(x_i,W),y_i)+\lambda{R(W)}$$
  - L2 regularization: $R(W)=\sum_k\sum_lW_{k,l}^2$
  - L1 regularization: $R(W)=\sum_k\sum_l|W_{k,l}|$
  - Elastic net (L1 + L2): $R(W)=\sum_k\sum_l\beta{W_{k,l}^2}+|W_{k,l}|$
  - Dropout, Batch normalization, Stochastic depth, fractional pooling, etc
- Softmax Classifier (Multinomial Logistic Regression)
  - Softmax Function: $P(Y=k|X=x_i)=\frac{e^{s_k}}{\sum_j{e^{s_j}}}$
  - $L_i=-log(\frac{e^{s_k}}{\sum_j{e^{s_j}}})$
  - Loss Function: $$L=\frac{1}{N}\sum_{i=1}^NL_i=-\frac{1}{N}log(\frac{e^{s_k}}{\sum_j{e^{s_j}}})$$
- Stochastic Gradient Descent (SGD) is:
  - On-line Gradient Descent
  - Minibatch Gradient Descent (MGD)
  - Batch gradient descent (BGD)
- Image Features

Lecture 4 | Introduction to Neural Networks

- Gradient
  - Numerical gradient: slow 😦, approximate 😦, easy to write 😃
  - Analytic gradient: fast 😃, exact 😃, error-prone 😦
- Computational graphs
  - Patterns in Gradient Flow



- How to compute gradients?
  - Computational graphs + Backpropagation
    - backprop with scalars
    - vector-valued functions

Lecture 5 | Convolutional Neural Networks

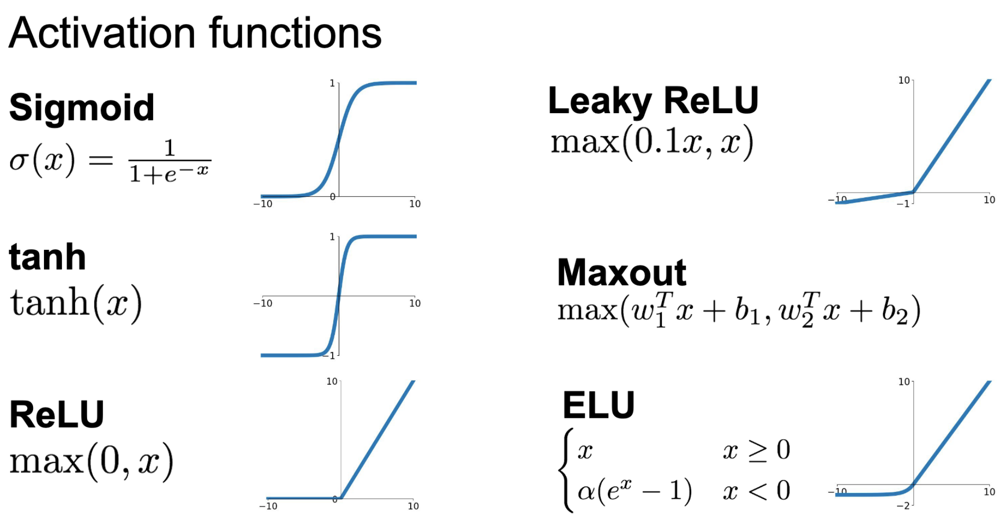
- Fully Connected Layer
- Convolution Layer
  - Accepts a volumne of size $W H D$
  - Hyperpararmeters
    - $K:\ number\ of\ filters$
    - $F:\ spatial\ extent\ of\ filter$
    - $S:\ stride$
    - $P:\ zero\ padding$
  - Produces a volume of size
    - $W=(W-F+2P)/S+1$
    - $H=(H-F+2P)/S+1$
    - $D=K$
  - The number of parameters: $(F·F·D)·K+K$
  - Pooling:
    - $W=(W-F)/S+1$
    - $H=(H-F)/S+1$
    - $D=D$

Lecture 6 | Training Neural Networks I

> Mini-batch SGD Loop:

> 1. **Sample** a batch of data
> 2. **Forward** prop it through the graph (network), get loss
> 3. **Backprop** to calculate the gradients
> 4. **Update** the parameters using the gradient

Activation Functions (Use ReLU)



- Sigmoid problems
    1. Saturated neurons “kill” the gradients
    2. Sigmoid outputs are not zero-centered
    3. exp() is a bit compute expensive
- tanh problems
    1. still kills gradients when saturated
- ReLU problems
    1. Not zero-centered output
- Leaky ReLU
    1. Does not saturate-
    2. Computationally efficient-
    3. Converges much faster than sigmoid/tanh in practice! (e.g. 6x)-
    4. will not “die”
- Parametric Rectifier (PReLU)
- Exponential Linear Units (ELU)
    - All benefits of ReLU-Closer to zero mean outputs
    - Negative saturation regime compared with Leaky ReLU adds some robustness to noise
- Maxout “Neuron”

> Use ReLU. Be careful with your learning rates Try out Leaky ReLU / Maxout / ELU Try out tanh but don’t expect much Don’t use sigmoid

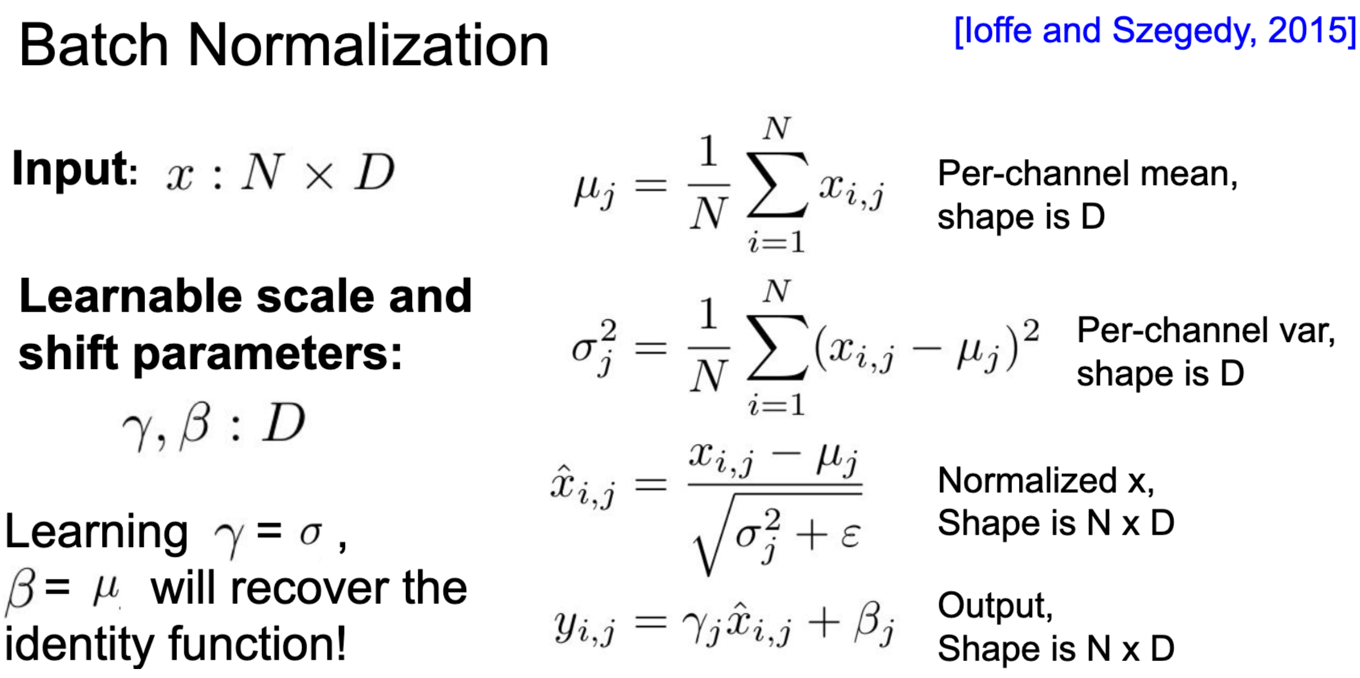
Data Preprocessing (Images: subtract mean)

- **zero-centered** (image only this)
- **normalized data**
- PCA
- Whitening

Weight Initialization (Use Xavier/He init/MSRA)

- tanh + "Xavier" Initialization: std = 1/sqrt(Din)
- ReLU + He et al. Initialization: std = sqrt(Din / 2)
- ReLU + Kaiming / MSRA Initialization: std = sqrt(2 / Din)

Batch Normalization (Use)



Babysitting the Learning Process

1. Double checkout the loss is reasonable
2. learning rate: 1e-5 ~ 1e-3

Hyperparameter Optimization

1. Only run a few epochs first
2. If the cost is ever > 3 * original cost, breat out
3. Random Search Hyperparameter > Grid Search Hyperparameter

Lecture 7 | Training Neural Networks II

Fancier optimization

> - **Adam** is a good default choice in many cases; it often works ok even with constant learning rate
> - **SGD + Momentum** can outperform Adam but may require more tuning of LR and schedule
>   - Try cosine schedule, very few hyperparameters!
> - If you can afford to do full batch updates then try out **L-BFGS** (and don't forget to disable all sources of noise)

- Problems with SGD (梯度方向？)

    1. Loss function has high condition number

        - ratio of largest to smallest singular value of the Hessian matrix is large

    2. Local minima / Saddle points

    3. Our gradients come from minibatches so they can be noisy

> SGD: $x_{t+1}=x_t-\alpha{\triangledown f(x_t)}$ SGD + Momentum: $x_{t+1}=x_t-\alpha{(\rho{v_t}+\triangledown f(x_t))}$ SGD + Nesterov Momentum: $x_{t+1}=x_t+\rho{v_t}-\alpha{\triangledown f(x_t+\rho{v_t})}$

- AdaGrad => RMSProp (Leaky AdaGrad) (梯度大小)

AdaGrad

```
grad_squared = 0
while True:
  dx = compute_gradient(x)
  grad_squared += dx * dx
  x -= learning_rate * dx / (np.sqrt(grad_squared) + 1e-7)
```

RMSProp

```
grad_squared = 0
while True:
  dx = compute_gradient(x)
  grad_squared = decay_rate * grad_squared + (1 - decay_rate) * dx * dx
  x -= learning_rate * dx / (np.sqrt(grad_squared) + 1e-7)
```

- Adam (almost)

Adam (full form)

```
first_moment = 0
second_moment = 0
for t in range(1, num_iterations):
  dx = compute_gradient(x)
  first_moment = beta1 * first_moment  + (1 - beta1) * dx
  second_moment = beta2 * second_moment + (1 - beta2) * dx * dx
  first_unbias = first_moment / (1 - beta1 ** t)
  second_unbias = second_moment / (1 - beta2 ** t)
  x -= learning_rate * first_unbias / (np.sqrt(second_unbias) + 1e-7))
```

Momentum

Bias correction

AdaGrad / RMSProp

- Learning Rate Decay (common with momentum & less common with Adam)

Cosine: $\alpha_t = \frac{1}{2}\alpha_0\left(1+\cos(t\pi/T)\right)$

Linear: $\alpha_t = \alpha_0(1-t/T)$

Inverse sqrt: $\alpha_t = \alpha_0/\sqrt{t}$

- Second-Order Optimization (without learning rate)
    - First-Order Optimization
        1. Use gradient form linear approximation
        2. Step to minimize the approximation

1. Use gradient and Hessian to form quadratic approximation
2. Step to the minima of the approximation

second-order Taylor expansion:

$$J(\boldsymbol{\theta}) \approx J(\boldsymbol{\theta}_0) + (\boldsymbol{\theta} - \boldsymbol{\theta}_0)^\top \nabla_{\boldsymbol{\theta}} J(\boldsymbol{\theta}_0) + \frac{1}{2}(\boldsymbol{\theta} - \boldsymbol{\theta}_0)^\top \boldsymbol{H}(\boldsymbol{\theta} - \boldsymbol{\theta}_0)$$

Solving for the critical point we obtain the Newton parameter update:

$$\boldsymbol{\theta}^* = \boldsymbol{\theta}_0 - \boldsymbol{H}^{-1} \nabla_{\boldsymbol{\theta}} J(\boldsymbol{\theta}_0)$$

Hessian has O(N^2) elements
Inverting takes O(N^3)
N = (Tens or Hundreds of) Millions

- Model Ensembles: Tips and Tricks

Regularization

- Add term to loss
- Dropout: In each forward pass, randomly set some neurons to zero
  - Probability of dropping is a hyperparameter; 0.5 is common
- Batch Normalization
- Data Augmentation
  - Horizontal Flips
  - Random crops and scales
  - Color Jitter
    - Simple: Randomize contrast and brightness
    - Complex: Apply PCA to all [R, G, B]
  - Random mix/combinations of:
    - translation, rotation, stretching, shearing, lens distortions
- DropConnect (set weights to 0)
- Fractional Max Pooling
- Stochastic Depth
- Cutout
- Mixup

Tansfer learning

	very similar dataset	**very different dataset**
very little data	Use Linear Classifier on top layer	You're in trouble... Try linear classifier from different stages
quite a lot of data	Finetune a few layers	Finetune a larger number of layers

Have some dataset of interest but it has < ~1M images?

1. Find a very large dataset that has similar data, train a big ConvNet there
2. Transfer learn to your dataset

Deep learning frameworks provide a “Model Zoo” of pretrained models so you don’t need to train your own Caffe: https://github.com/BVLC/caffe/wiki/Model-Zoo TensorFlow: https://github.com/tensorflow/models PyTorch: https://github.com/pytorch/vision

Choosing Hyperparameters

1. Check initial loss
2. Overfit a small sample
3. Find LR that makes loss go down
4. Coarse grid, train for ~1-5 epochs
5. Refine grid, train longer
6. Look at loss curves