CSC520 - Artificial Intelligence Lecture 25

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Agenda

- Computer vision tasks
- Convolution operation
- Padding and stride
- Convolution layer
- Pooling layer
- LeNet-5 Model

Computer Vision

 Computer vision's goal is to enable computers to interpret and understand images

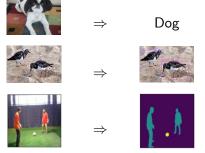


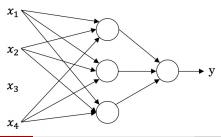
Image captioning Face recognition Object tracking Human pose recognition

Fully-connected NN for Computer Vision Tasks

• Colored image is a 3-D (width x height x 3) grid of pixels

| 8 | 9 | 2 | 4 | 3 |
|---|---|---|---|---|
| 6 | 5 | 3 | 7 | 9 |
| 1 | 0 | 8 | 9 | 3 |
| 4 | 2 | 6 | 3 | 2 |
| 8 | 4 | 2 | 0 | 1 |
| 2 | 1 | 8 | 9 | 0 |

• For a 1000×1000 image, the number of features: $1000 \times 1000 \times 3 = 3M$

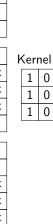


Convolution Operation

| Х | х | Х | | |
|---|---|---|---|--|
| Х | Х | Х | | |
| Х | Х | Х | - | |
| | | | | |
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| | | | | |
| Х | Х | Х | | |
| Х | Х | Х | | |
| Х | Х | Х | | |
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| | | | | |
| | | | | |
| | | | | |
| Х | Х | Х | | |
| Х | Х | X | | |
| Х | Х | X | | |
| | | | | |

| | X | X | X | |
|---|---|---|---|--|
| | × | х | Х | |
| | | | | |
| | | | | |
| | • | • | | |
| | | | | |
| | × | х | Х | |
| | Х | Х | Х | |
| | х | Х | Х | |
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| | | | | |
| | Х | Х | Х | |
| - | Х | Х | Х | |
| | Х | Х | Х | |

| • | ٠. | X | X | X | |
|---|----|---|---|---|--|
| | | Х | Х | Х | |
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| | | Х | Х | х | |
| | | Х | Х | Х | |
| | | Х | Х | Х | |
| | | | | | |
| | | | | | |
| | | | | | |
| | | | | | |
| | | Х | X | Х | |
| | | Х | X | Х | |
| | | Х | Х | Х | |



Output

| | Σ | \sum | \sum |
|---|---|--------|--------|
| | Σ | \sum | Σ |
| J | Σ | Σ | Σ |

Convolution Operation

| 8 | 9 | 2 | 4 | 3 | 2 |
|---|---|---|---|---|---|
| 6 | 5 | 3 | 7 | 9 | 8 |
| 1 | 0 | 8 | 9 | 3 | 1 |
| 4 | 2 | 6 | 3 | 2 | 0 |
| 8 | 4 | 2 | 0 | 1 | 2 |
| 2 | 1 | 8 | 9 | 0 | 1 |

| 1 | 0 | -1 |
|---|---|----|
| 1 | 0 | -1 |
| 1 | 0 | -1 |

| | | -2 | 9 |
|----|-----|----|----|
| -6 | -12 | 3 | 10 |
| -3 | -6 | 10 | 9 |
| -2 | -5 | 13 | 9 |

Edge Detection using Convolution

| 15 | 15 | 15 | 0 | 0 | 0 |
|----|----|----|----|----|----|
| 15 | 15 | 15 | 0 | 0 | 0 |
| 15 | 15 | 15 | 0 | 0 | 0 |
| 15 | 15 | 15 | 15 | 15 | 15 |
| 15 | 15 | 15 | 15 | 15 | 15 |
| 15 | 15 | 15 | 15 | 15 | 15 |

| 1 | 0 | -1 |
|---|---|----|
| 1 | 0 | -1 |
| 1 | 0 | -1 |

| 1 | 1 | 1 |
|----|----|----|
| 0 | 0 | 0 |
| -1 | -1 | -1 |

| 0 | 45 | 45 | 0 |
|---|----|----|---|
| 0 | 30 | 30 | 0 |
| 0 | 15 | 15 | 0 |
| 0 | 0 | 0 | 0 |

| 0 | 0 | 0 | 0 |
|---|-----|-----|-----|
| 0 | -15 | -30 | -45 |
| 0 | -15 | -30 | -45 |
| 0 | 0 | 0 | 0 |

Edge Detection Example







Padding

- Convolving an image with a filter may reduce the size of the output
 - Causes loss of information from the image borders
- Image is padded with a border to address this issue
 - Pixels in the padded region are typically set to 0

| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
|---|---|---|---|---|---|---|---|
| 0 | 8 | 9 | 2 | 4 | 3 | 2 | 0 |
| 0 | 6 | 5 | 3 | 7 | 9 | 8 | 0 |
| 0 | 1 | 0 | 8 | 9 | 3 | 1 | 0 |
| 0 | 4 | 2 | 6 | 3 | 2 | 0 | 0 |
| 0 | 8 | 4 | 2 | 0 | 1 | 2 | 0 |
| 0 | 2 | 1 | 8 | 9 | 0 | 1 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

|) -1 |
|--------|
|) -1 |
|) -1 |
| |

| -14 | 9 | 3 | -7 | 1 | 12 |
|-----|----|-----|----|----|----|
| -14 | 2 | -6 | -2 | 9 | 15 |
| -7 | -6 | -12 | 3 | 10 | 14 |
| -6 | -3 | -6 | 10 | 9 | 6 |
| -7 | -2 | -5 | 13 | 9 | 3 |
| -5 | 0 | -4 | 9 | 6 | 1 |

Padding

- If image size is h x w, filter size is f x f, and padding size is p, then the output size is: $(h+2p-f+1) \times (w+2p-f+1)$
- Valid convolution means no padding is added
- Same convolution means image is padded such that output size equals image size

Stride

- Filter is moved over the image in steps equal to stride value
- Suppose stride = 2

| 1 | 0 | • | -1 | |
|---|---|---|----|--|
| | | | | |
| 1 | 0 | | -1 | |
| | | | | |
| 1 | 0 | | -1 | |
| | | | | |
| | | | | |

| 1 | 0 | -1 |
|---|---|----|
| 1 | 0 | -1 |
| 1 | 0 | -1 |

Stride

- Filter is moved over the image in steps equal to stride value
- Suppose stride = 2

| 8 | 9 | 2 | 4 | 3 | 2 | 1 |
|---|---|---|---|---|---|---|
| 6 | 5 | 3 | 7 | 9 | 8 | 0 |
| 1 | 0 | 8 | 9 | 3 | 1 | 3 |
| 4 | 2 | 6 | 3 | 2 | 0 | 4 |
| 8 | 4 | 2 | 0 | 1 | 2 | 2 |
| 2 | 1 | 8 | 9 | 0 | 1 | 1 |
| 3 | 2 | 1 | 4 | 1 | 2 | 0 |

| 1 | 0 | -1 |
|---|---|----|
| 1 | 0 | -1 |
| 1 | 0 | -1 |

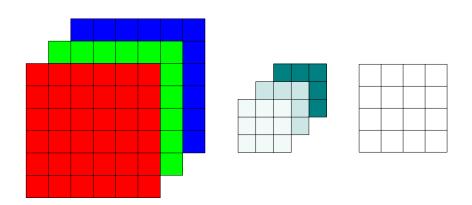
| | | 11 |
|----|----|----|
| -3 | 10 | -3 |
| 2 | 9 | -1 |

Output Size Calculation

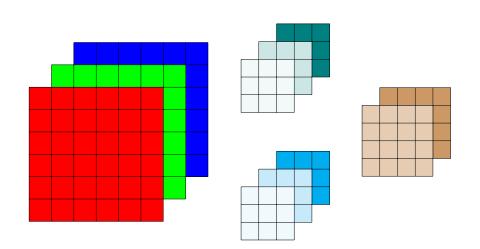
- Input size $= h \times w$
- Filter size = f
- Padding = p
- Stride = s
- Output size can be calculated using this formula:

$$\left\lfloor \frac{h+2p-f}{s} + 1 \right\rfloor \times \left\lfloor \frac{w+2p-f}{s} + 1 \right\rfloor$$

3D Convolution



3D Convolution



Convolution Layer

- Input dimensions: $h_{\ell-1} imes w_{\ell-1} imes c_{\ell-1}$
- Filter size: f_{ℓ} , number of filters: c_{ℓ} , padding: p_{ℓ} , stride: s_{ℓ}
- Output dimensions: $h_{\ell} \times w_{\ell} \times c_{\ell}$

$$egin{aligned} h_\ell &= \left\lfloor rac{h_{\ell-1} + 2p_\ell - f_\ell}{s_\ell} + 1
ight
floor \ w_\ell &= \left\lfloor rac{w_{\ell-1} + 2p_\ell - f_\ell}{s_\ell} + 1
ight
floor \end{aligned}$$

- ullet Number of parameters in one filter $= (f_\ell imes f_\ell imes c_{\ell-1}) + 1$
- ullet Total number of parameters $= [(f_\ell imes f_\ell imes c_{\ell-1}) + 1] imes c_\ell$

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Pooling Layer In Convolutional NN

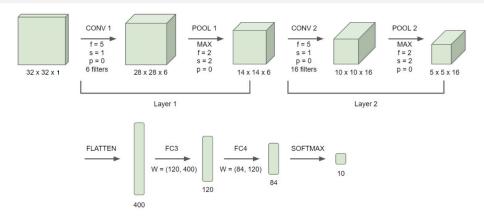
- Hyperparameters are: filter size, padding, stride
- No parameters to learn
- Two variants: max pooling and average pooling
- ullet Example of max pooling where f=2 and s=2

| 2 | 4 | 3 | 5 | 3 | 2 |
|---|---|---|---|---|---|
| 3 | 5 | 3 | 7 | 2 | 1 |
| 1 | 0 | 8 | 9 | 9 | 1 |
| 4 | 2 | 4 | 8 | 2 | 0 |
| 3 | 4 | 2 | 0 | 1 | 2 |
| 2 | 1 | 1 | 2 | 0 | 1 |

| | | 3 |
|---|---|---|
| 4 | 9 | 9 |
| 4 | 2 | 2 |

• Same formula as earlier can be used to calculate the output size

LeNet-5 CNN



LeNet-5 CNN

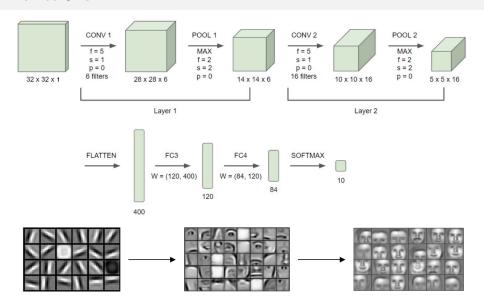


Image credit: Andrew Ng

LeNet-5 CNN Parameters

| Layer | Shape | Parameters |
|---------|--------------------------|---------------------------|
| Input | 32 × 32 × 1 | 0 |
| CONV1 | $28 \times 28 \times 6$ | (5*5*1+1)*6=156 |
| POOL1 | $14 \times 14 \times 6$ | 0 |
| CONV2 | $10 \times 10 \times 16$ | (5*5*6+1)*16=2416 |
| POOL2 | $5 \times 5 \times 16$ | 0 |
| FC3 | 120 | (400 * 120) + 120 = 48120 |
| FC4 | 84 | (120 * 84) + 84 = 10164 |
| Softmax | 10 | (84*10) + 10 = 850 |

Training CNN

- Can be trained using gradient descent algorithm
 - Initialize weights and baises
 - Compute activations in the forward pass
 - Compute gradient in the backward pass
 - Update weights and baises to minimize the loss
- Same loss functions we discussed earlier are used
 - Mean squared error for regression tasks

*
$$MSE = \frac{1}{m} \sum_{i=1}^{m} (y_i - \hat{y}_i)^2$$

- Cross-entropy loss for classification tasks
 - * Logloss = $-\frac{1}{m}\sum_{i=1}^{m}\sum_{j=1}^{k}y_{ij}\log(\hat{y}_{ij})$

Class Exercise

• Calculate the result of following convolution operation. Assume p=0 and s=1.

| 8 | 9 | 2 | 4 | 3 | 2 |
|---|---|---|---|---|---|
| 6 | 5 | 3 | 7 | 9 | 8 |
| 1 | 0 | 8 | 9 | 3 | 1 |
| 4 | 2 | 6 | 3 | 2 | 0 |
| 8 | 4 | 2 | 0 | 1 | 2 |
| 2 | 1 | 8 | 9 | 0 | 1 |

| 1 | 1 | 1 | |
|----|----|----|--|
| 0 | 0 | 0 | |
| -1 | -1 | -1 | |