

(a)

- Input: 32x32x3
- Conv1: 28x28x16
- MaxPool1: 14x14
- Conv2: 12x12x32
- MaxPool2: 6x6x32
- Fully connected: 128
- Output: 10

(b)

- Conv1:  $5*5*16(\text{filters}) + 16(\text{biases})=1216$
- Conv2:  $3*3*32(\text{filters}) + 32(\text{biases})=1472$
- Fully connected:
  - inputs from MaxPool2 =  $6*6*32=1152$
  - biases: 128
  - total:  $1152*128+128=147584$

\*Output:  $128*10+10(\text{biases}) = 1290$

Total:  $1216 + 1472 + 147584 + 1290 = \mathbf{151562}$

(c)

### Forward Pass Normalization:

$x$  as the input to the batch normalization layer (output of Conv1 in this case)

$\mu_B$  as the mean of the input batch:  $\mu_B = (1/m)*\sum(x_i)$  ( $m$  is the batch size)

$\sigma_B^2$  as the variance of the input batch:  $\sigma_B^2 = (1/m)*\sum(x_i - \mu_B)^2$

$\epsilon$  as a small constant for numerical stability

$\gamma$  as the scale parameter (learnable)

$\beta$  as the shift parameter (learnable)

Input normalization:  $\bar{x} = (x_i - \mu_B) / \sqrt{(\sigma_B^2 + \epsilon)}$

Scale and shift:  $y_i = \gamma * \bar{x} + \beta$

### Backpropagation:

Gradient with respect to  $y_i$  :

$$\partial L / \partial \bar{x} = \partial L / \partial y_i * \gamma \quad \partial L / \partial \beta = \sum(\partial L / \partial y_i)$$

Gradient with respect to  $x_i$  :

$$\partial L / \partial x_i = \partial L / \partial \bar{x} * (1/m) * (1/\sqrt{(\sigma_B^2 + \epsilon)}) * (m - (x_i - \mu_B) * (1/m) * \sum(\partial L / \partial \bar{x}))$$

Gradient with respect to  $\gamma$ :

$$\partial L / \partial \gamma = \sum(\partial L / \partial y_i * \bar{x})$$

Gradient with respect to  $\beta$ :

$$\partial L / \partial \beta = \sum(\partial L / \partial y_i)$$