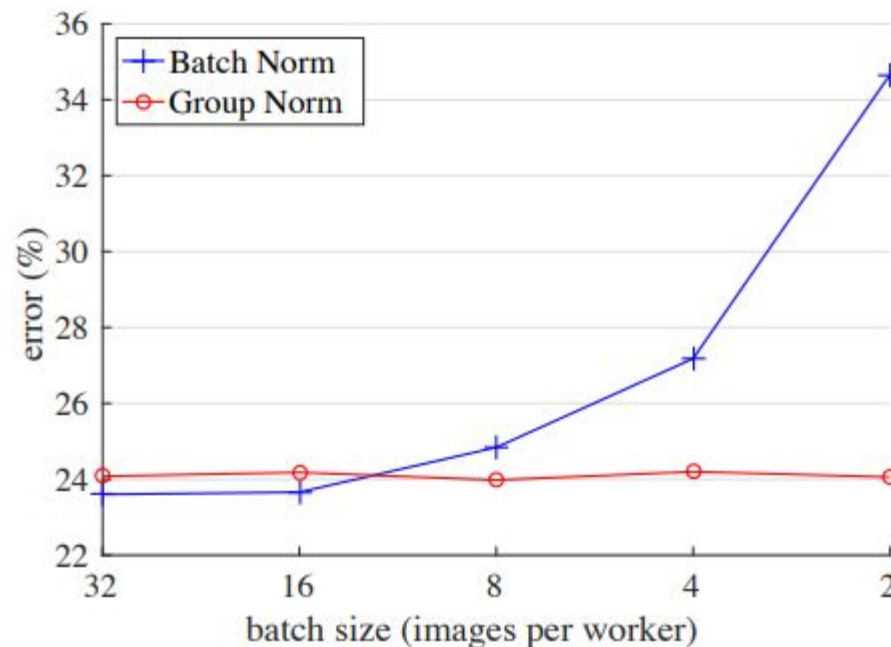


# Group Normalization

Presenter: Baosong Yang

# Motivation

- Batch Normalization:
  - Error increases rapidly when the batch size becomes smaller (OOM)
  - The batch sizes are inconsistent in training and testing (mean and variance)
  - How to avoid normalizing the batch?



# Normalization

- Shift and scale to get standard distribution

$$\hat{x}_i = \frac{1}{\sigma_i}(x_i - \mu_i), \quad \mu_i = \frac{1}{m} \sum_{k \in \mathcal{S}_i} x_k, \quad \sigma_i = \sqrt{\frac{1}{m} \sum_{k \in \mathcal{S}_i} (x_k - \mu_i)^2 + \epsilon},$$

- Re-shift and re-scale to guarantee the expressive

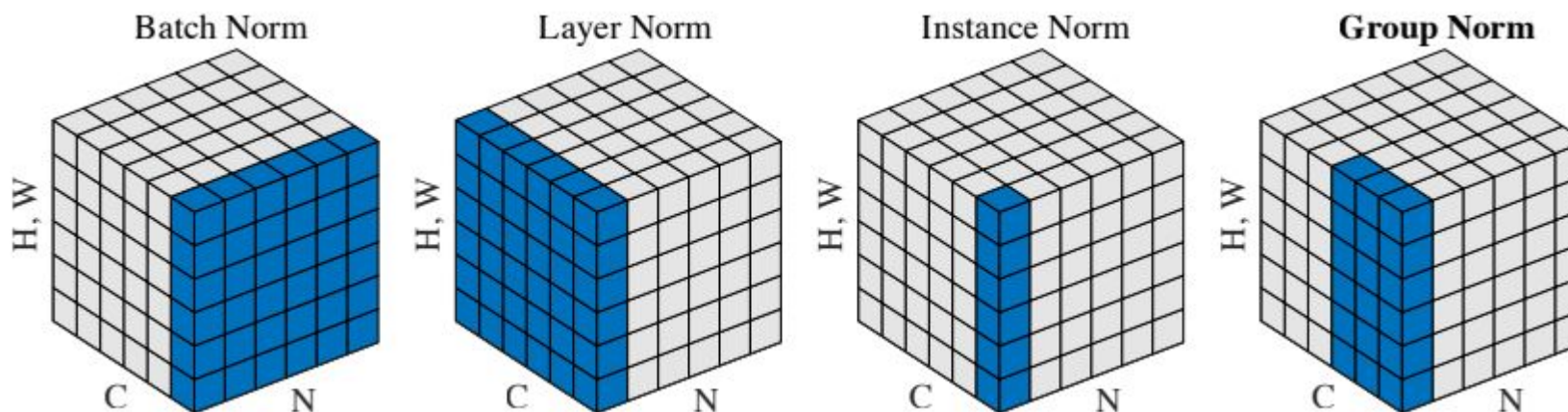
$$y_i = \gamma \hat{x}_i + \beta,$$

## GN

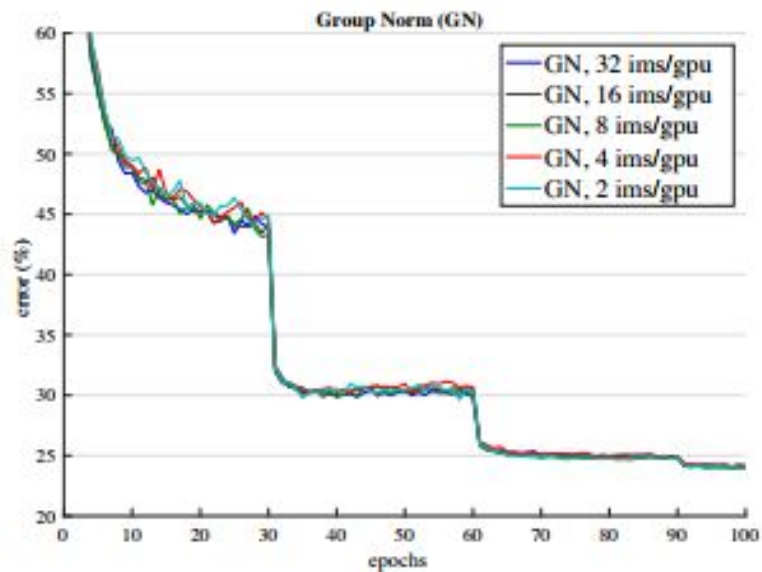
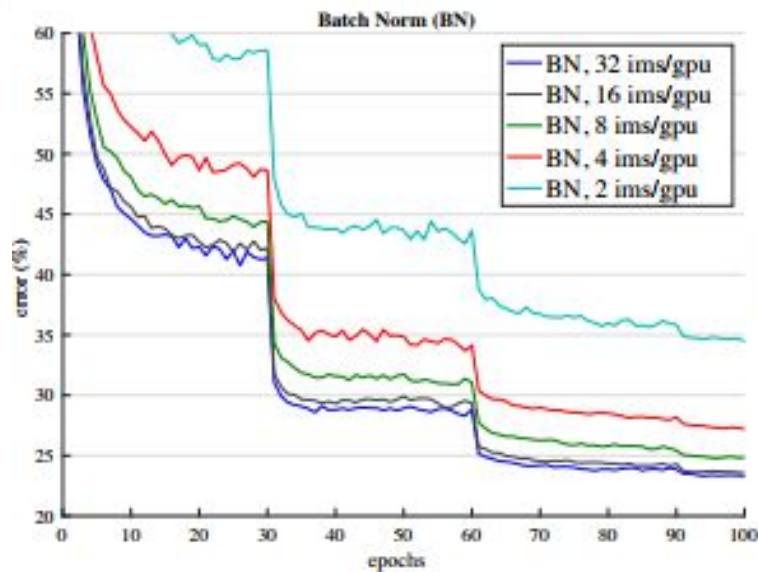
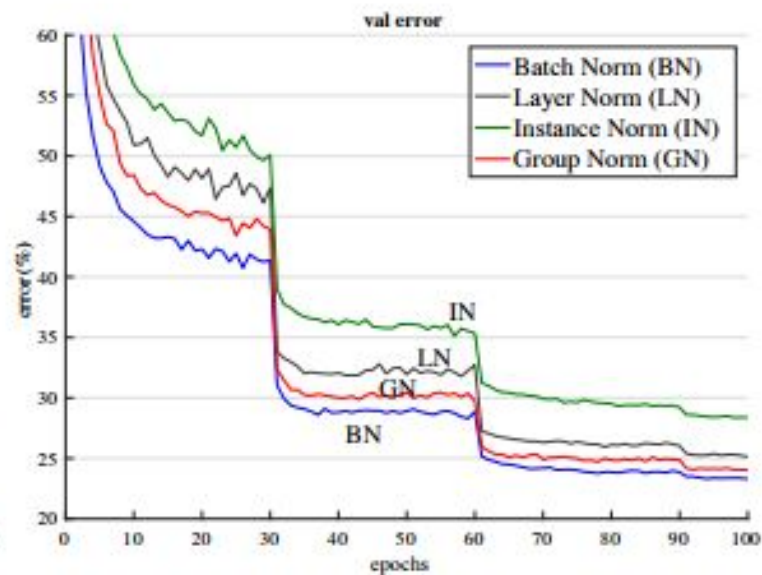
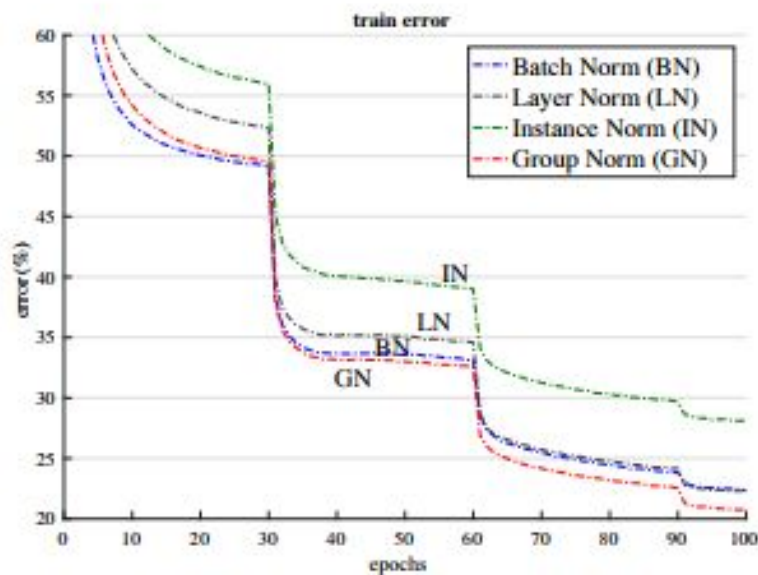
- GN divides the channels into groups.
- The mean and variance for normalization are computed within each group.
- GN's computation is independent of batch sizes.

# Comparing with other normalization

- Batch Normalization: [N, H, W]  $\mathcal{S}_i = \{k \mid k_C = i_C\},$
- Layer Normalization: [C, H, W]  $\mathcal{S}_i = \{k \mid k_N = i_N\}$
- Instance Normalization: [H, W]  $\mathcal{S}_i = \{k \mid k_N = i_N, k_C = i_C\}$
- Group Normalization: [C//G, H, W]  $\mathcal{S}_i = \{k \mid k_N = i_N, \lfloor \frac{k_C}{C/G} \rfloor = \lfloor \frac{i_C}{C/G} \rfloor\}.$



# Experiments



# Experiments

# groups ( $G$ )						
64	32	16	8	4	2	1 (=LN)
24.6	<b>24.1</b>	24.6	24.4	24.6	24.7	25.3
<i>0.5</i>	-	<i>0.5</i>	<i>0.3</i>	<i>0.5</i>	<i>0.6</i>	<i>1.2</i>

# channels per group						
64	32	16	8	4	2	1 (=IN)
24.4	24.5	<b>24.2</b>	24.3	24.8	25.6	28.4
<i>0.2</i>	<i>0.3</i>	-	<i>0.1</i>	<i>0.6</i>	<i>1.4</i>	<i>4.2</i>

Table 3. **Group division.** We show ResNet-50’s validation error (%) in ImageNet, trained with 32 images/GPU. (Top): a given number of groups. (Bottom): a given number of channels per group. The last rows show the differences with the best number.



# Conclusion

- GN is less restricted than LN (Why multi-head is better than single-head)
- IN misses the opportunity of exploiting the channel dependence. (A support for CSAN)
- Improving Transformer with Head Normalization?
- Why not normalize along length and batch?

```
def layer_norm(inputs, epsilon=1e-6, dtype=None, scope=None):  
    """  
    Layer Normalization  
    :param inputs: A Tensor of shape [..., channel_size]  
    :param epsilon: A floating number  
    :param dtype: An optional instance of tf.DType  
    :param scope: An optional string  
    :returns: A Tensor with the same shape as inputs  
    """  
    with tf.variable_scope(scope, default_name="layer_norm", values=[inputs],  
                           dtype=dtype):  
        channel_size = inputs.get_shape().as_list()[-1]  
  
        scale = tf.get_variable("scale", shape=[channel_size],  
                                initializer=tf.ones_initializer())  
  
        offset = tf.get_variable("offset", shape=[channel_size],  
                                  initializer=tf.zeros_initializer())  
  
        mean = tf.reduce_mean(inputs, axis=-1, keep_dims=True)  
        variance = tf.reduce_mean(tf.square(inputs - mean), axis=-1,  
                                   keep_dims=True)  
  
        norm_inputs = (inputs - mean) * tf.rsqrt(variance + epsilon)  
  
        return norm_inputs * scale + offset
```