Class Activation Map (CAM)

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Issues on CNN (or Deep Learning)

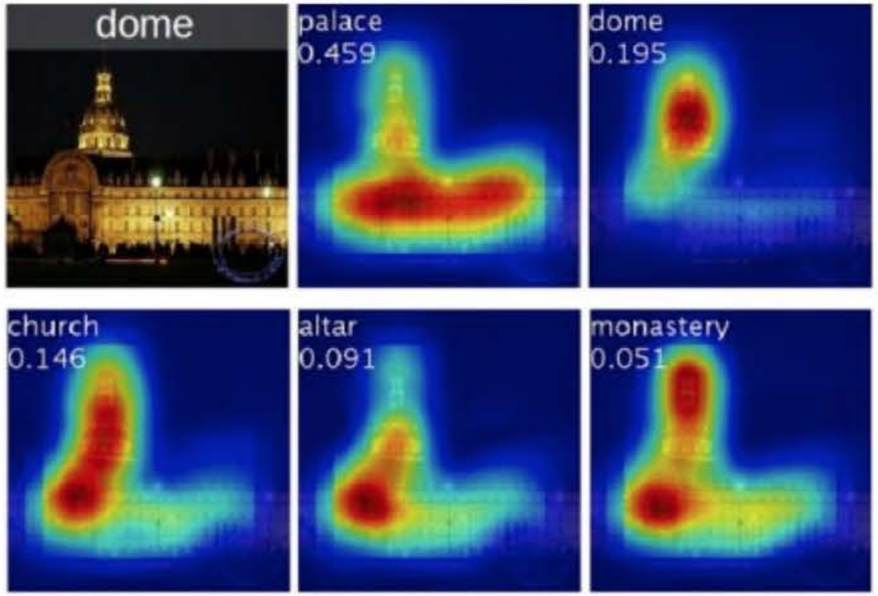
- Deep learning performs well comparing with any other existing algorithms
- But works as a black box
  - A classification result is simply returned without knowing how the classification results are derived → little interpretability

- When we visually identify images, we do not look at the whole image
- Instead, we intuitively focus on the most important parts of the image
- When CNN weights are optimized, the more important parts are given higher weights

- Class activation map (CAM)
  - We can determine which parts of the image the model is focusing on, based on the learned weights
  - Highlighting the importance of the image region to the prediction

Visualizing Convolutional Neural Networks

- Class Activation Maps (CAMs)
- A class activation map (CAM) for a given class highlights the image regions used by the CNN to identify that class



Class activation maps of top 5 predictions

Class activation maps for one object class

B. Zhou, A. Khosla, A. Lapedriza, A. Oliva, and A. Torralba.
Learning Deep Features for Discriminative Localization. CVPR'16

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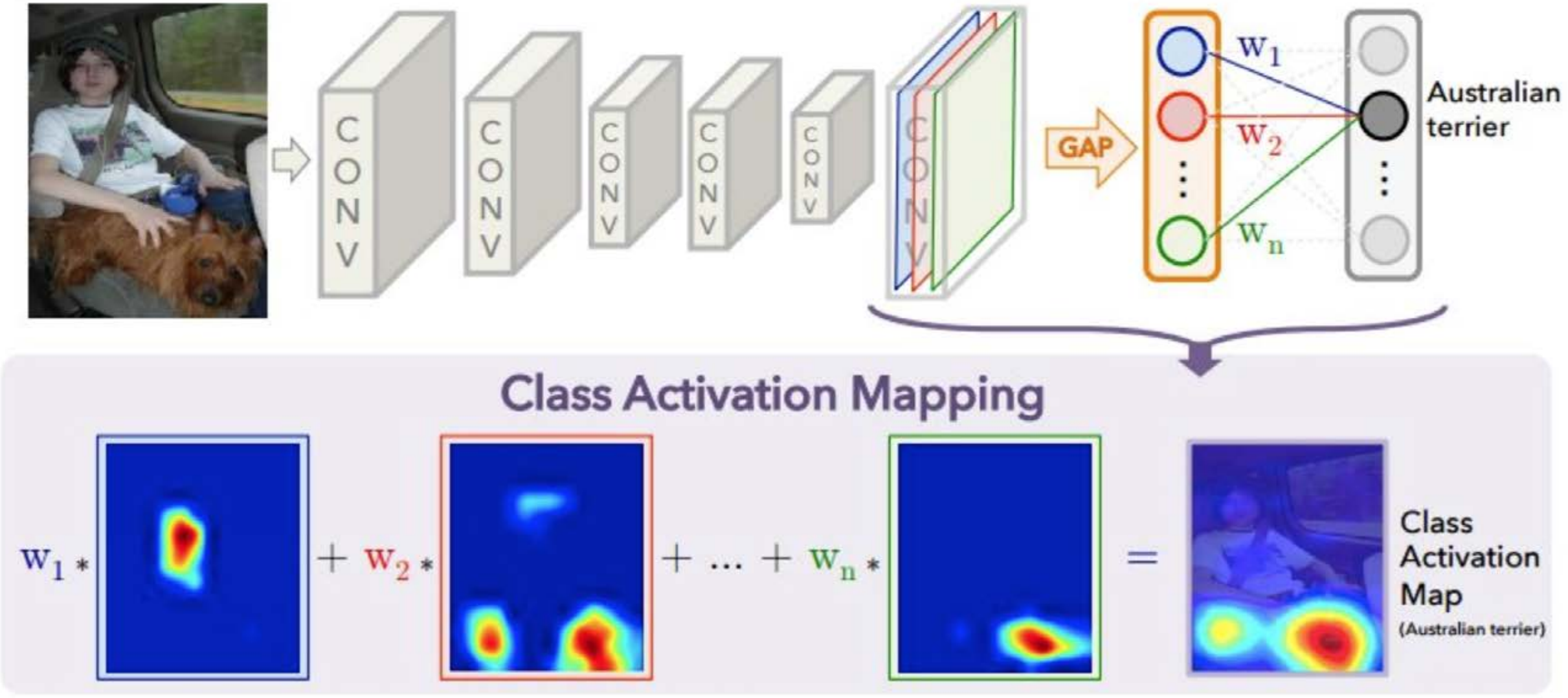

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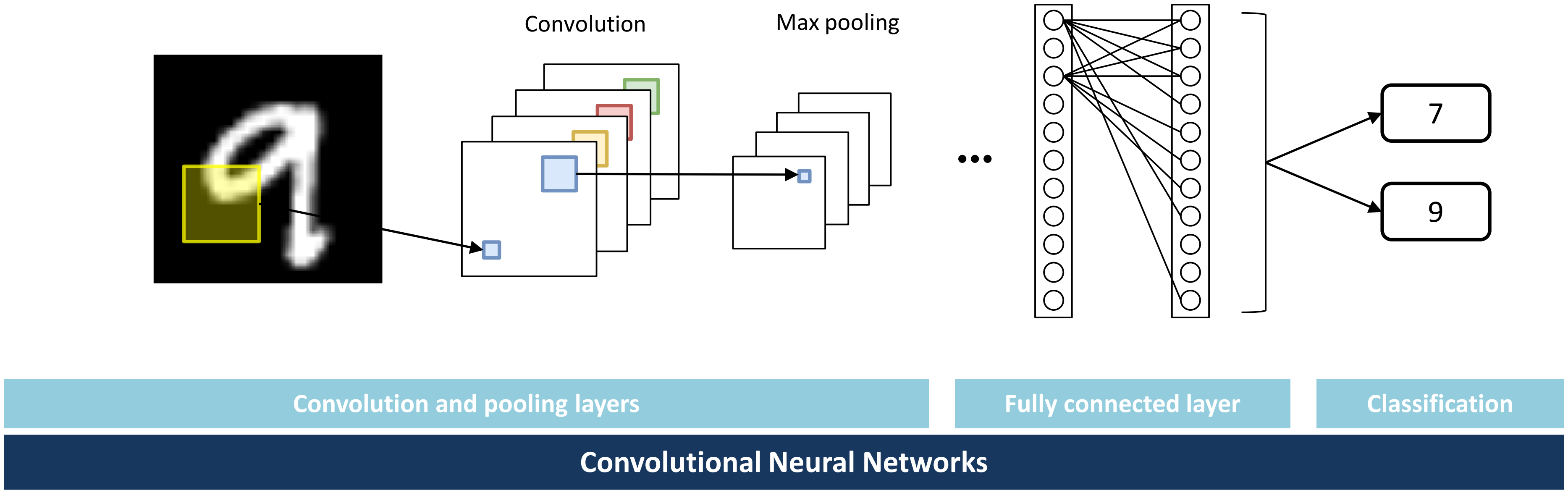
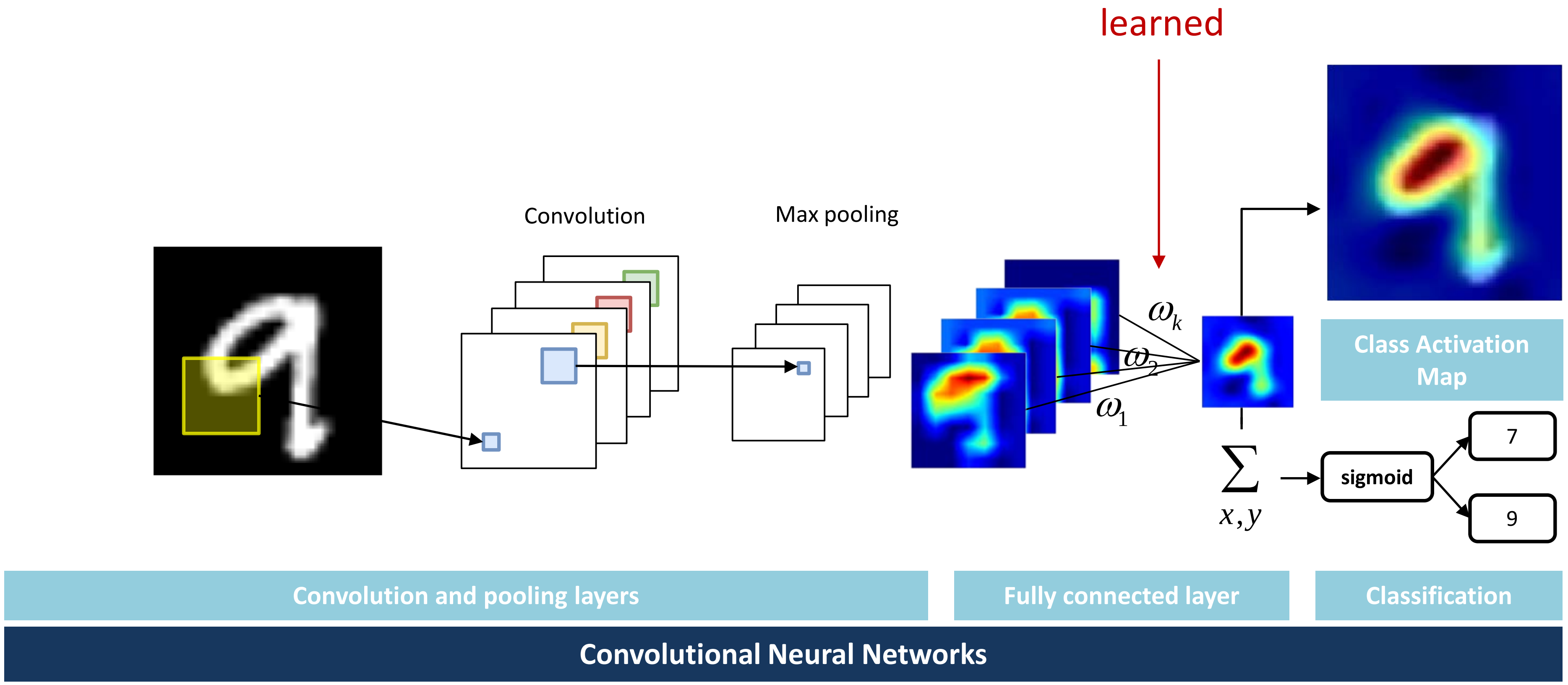
Fully Connected Layer



Global Average Pooling

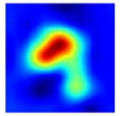
- Class Activation Map (or Attention)

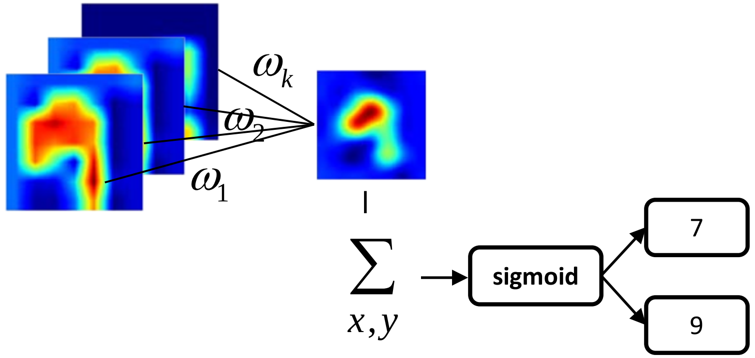


Global Average Pooling Implementation

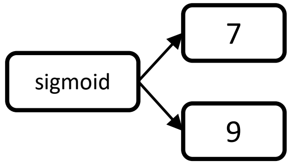
```python
## global average pooling
SUM = tf.zeros([1,7,7,1])
for i in range(int(weights['w'].shape[0])):
    SUM = tf.add(weights['w'][i]*tf.reshape(maxp2[:,:,:,i],(-1,7,7,1)), SUM)

attention = tf.reduce_sum(SUM, axis = (3))
output = tf.reduce_sum(attention, axis = (1,2))
output = tf.nn.sigmoid(output)
output = tf.stack(((1-output), output),1)
```

$$S_c = \sum_k \omega_k^c \sum_{x,y} f_k(x,y) = \sum_{x,y} \underbrace{\sum_k \omega_k^c \, f_k(x,y)}$$





$$P_c = \frac{\exp(S_c)}{\sum_c \exp(S_c)}$$

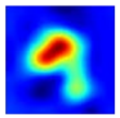


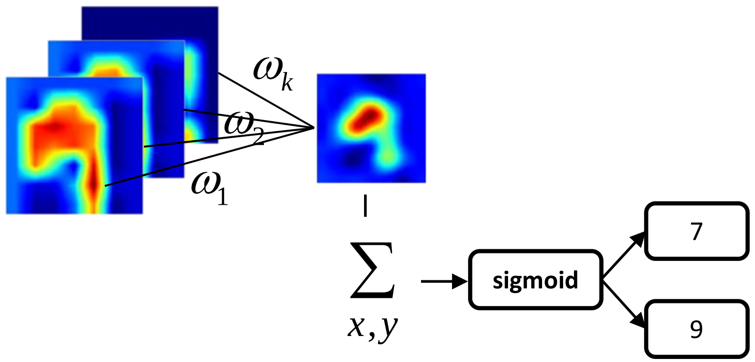
Global Average Pooling Implementation (Better Way)

```python
## global average pooling
avg = tf.reduce_mean(maxp2, axis = (1,2))
output = tf.matmul(avg, weights['output'])
```

```python
maps, pred = net(x, weights, biases)
loss = tf.nn.softmax_cross_entropy_with_logits(labels = y, logits = pred)
loss = tf.reduce_mean(loss)
```

$$S_c = \sum_k \omega_k^c \sum_{x,y} f_k(x,y) = \sum_{x,y} \sum_k \omega_k^c \, f_k(x,y)$$





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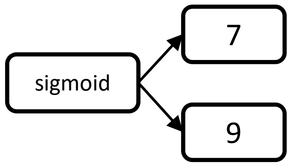
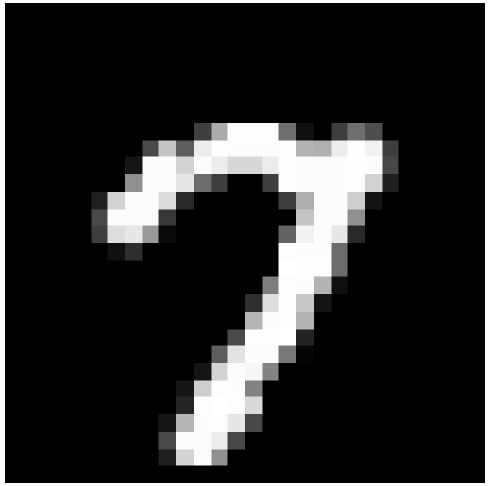
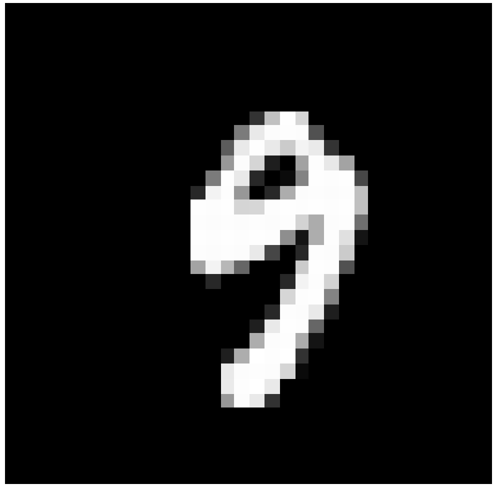


Example: MNIST





Example: Real-time Human Detection