E9: 309 ADL 16-12-2020

http://leap.ee.iisc.ac.in/sriram/teaching/ADL2020/

Recap from previous lectures

- Analyzing trained neural networks
  - ✓ Hierachical representations
    - ◉ Maximizing activations
    - ◉ Visualizing representations
    - ◉ Reconstruction of input patterns from hidden layers.

* Transferability of representations

Today's lecture

- ✴️ Why models predict what they predict

Architecture updates for interpretability

Learning Deep Features for Discriminative Localization

Bolei Zhou, Aditya Khosla, Agata Lapedriza, Aude Oliva, Antonio Torralba
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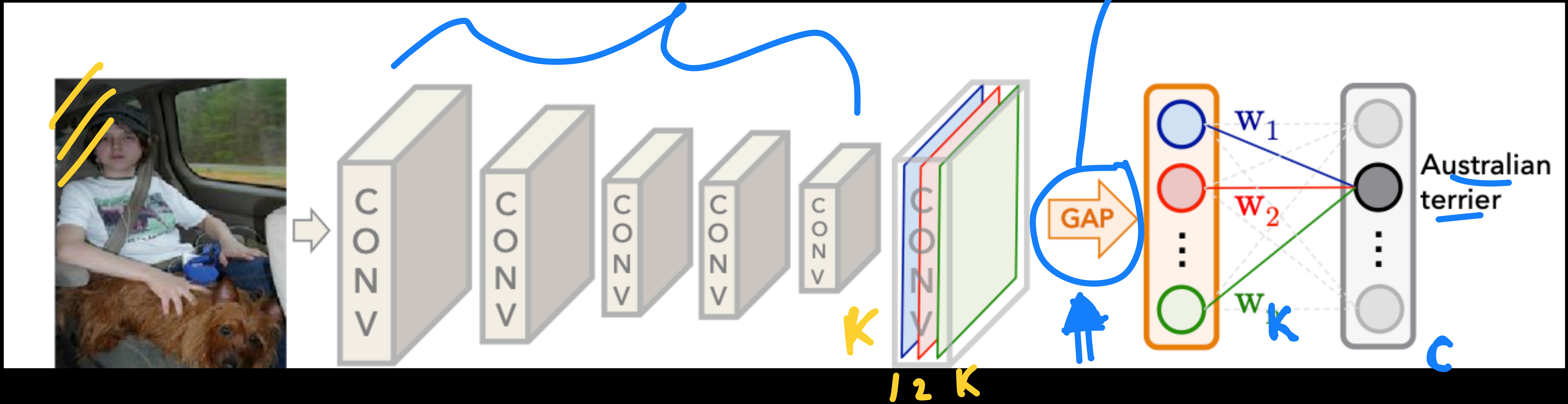
2015

Learning the input pattern of a trained network

Global average pooling



Architecture updates for interpretability

- Global average pooling

$$\boxed{F^{k,L} = \sum_{i,j} \mathbf{f}^{k,L}(i,j)}$$

k - index of feature map

$k = 1 .. K$

L - last layer

- Last layer mapping to classes

$$a^{c,L} = \sum_{k=1}^{K} w_c^{k,L} F^{k,L}$$

$$\hat{\mathbf{y}} = softmax(\mathbf{a}^L)$$

$$a^L = \begin{bmatrix} a^{1,L} \\ a^{c,L} \\ \vdots \\ a^{C,L} \end{bmatrix}$$

Architecture updates for interpretability

- Rearranging the terms

$$a^{c,L} = \sum_{k=1}^{K} w_c^{k,L} \overbrace{\sum_{i,j} \mathbf{f}^{k,L}(i,j)}^{\text{GAP}}$$

$$= \sum_{i,j} \underbrace{\sum_{k=1}^{K} w_c^{k,L} \mathbf{f}^{k,L}(i,j)}_{\text{Image}}$$

$a^{c,L}$ → output activation

- Defining the map

$$\mathbf{m}^{c}(i,j) = \underbrace{\sum_{k=1}^{K} w_c^{k,L} \mathbf{f}^{k,L}(i,j)}$$

Class activation maps

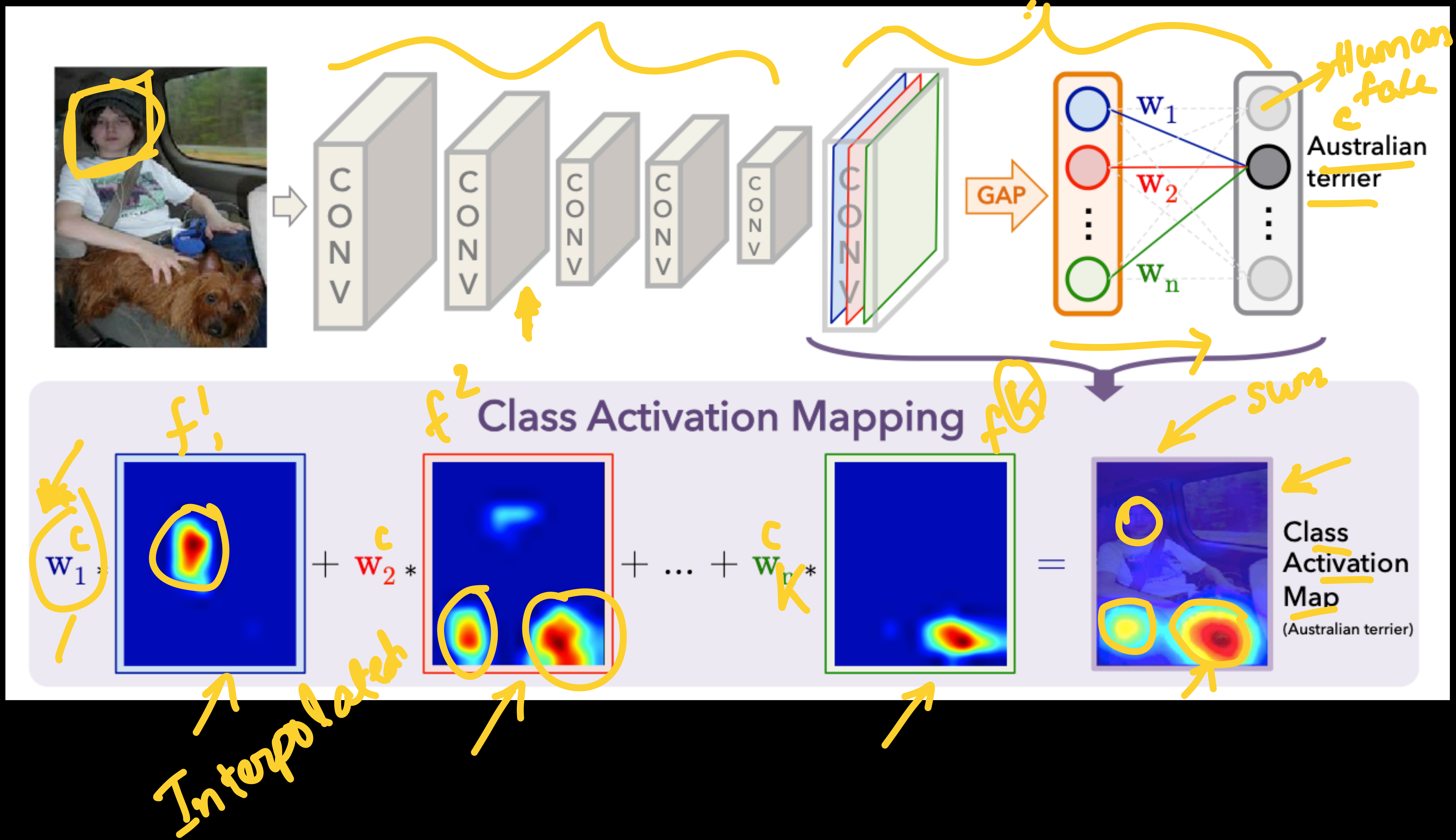
Architecture updates for interpretability

CAM

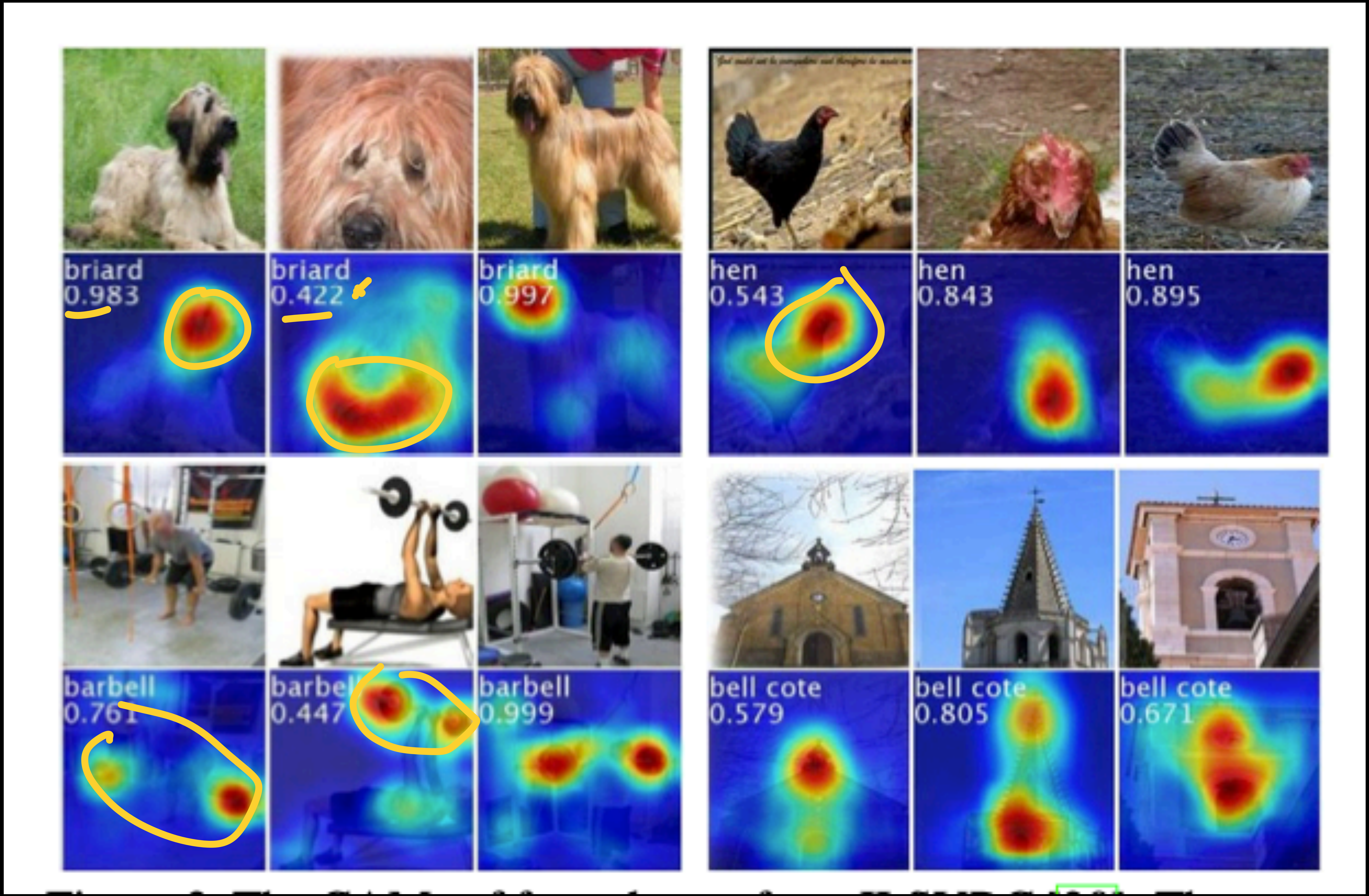
- The maps denote spatial patterns that define how important a particular pixel is for that particular class.

- The map can be interpolated to the original input dimensions to visualize the pattern

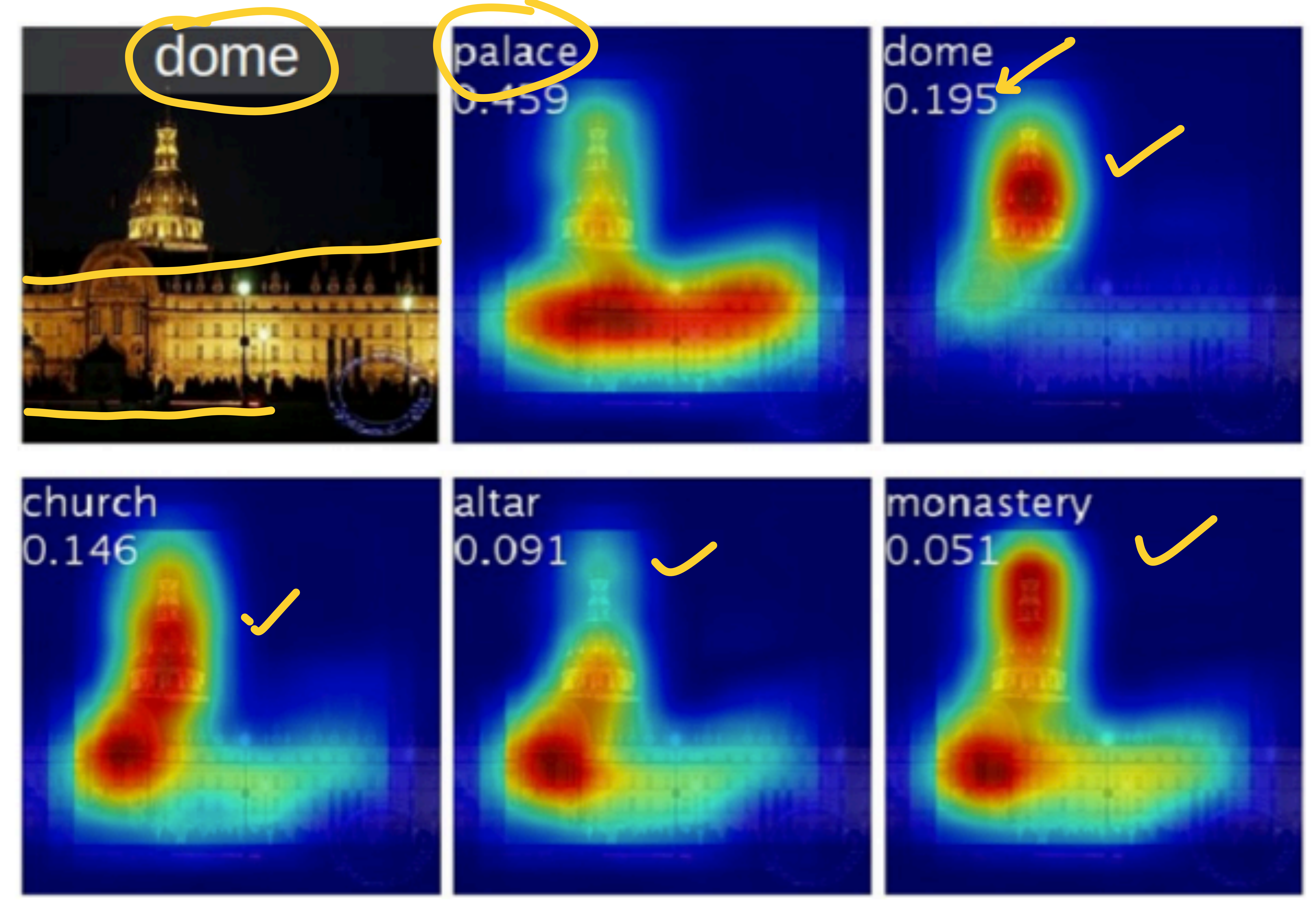
Architecture updates for interpretability



Architecture updates for interpretability



Architecture updates for interpretability



Architecture updates for interpretability

- Flaws in the approach
  - Requires Global average pooling based
  - The model may be inferior to the other models with fully connected layers after the CNN layers

Table 1. Classification error on the ILSVRC validation set.

Networks	top-1 val. error	top-5 val. error
VGGnet-GAP	33.4	12.2
GoogLeNet-GAP	35.0	13.2
AlexNet*-GAP	44.9	20.9
AlexNet-GAP	51.1	26.3
GoogLeNet	31.9	11.3
VGGnet	31.2	11.4
AlexNet	42.6	19.5

Grad-CAM : Visual Explanations ....

Selvaraju et. al (2016 CVPR)

Improving CAM without compromising architecture

- Find the gradient of the output activation with respect to the feature maps of the last convolutional layer

$$\alpha_k^c = \frac{1}{S} \sum_{i,j} \frac{\partial a^{c,L}}{\partial \mathbf{f}^{k,l}(i,j)}$$

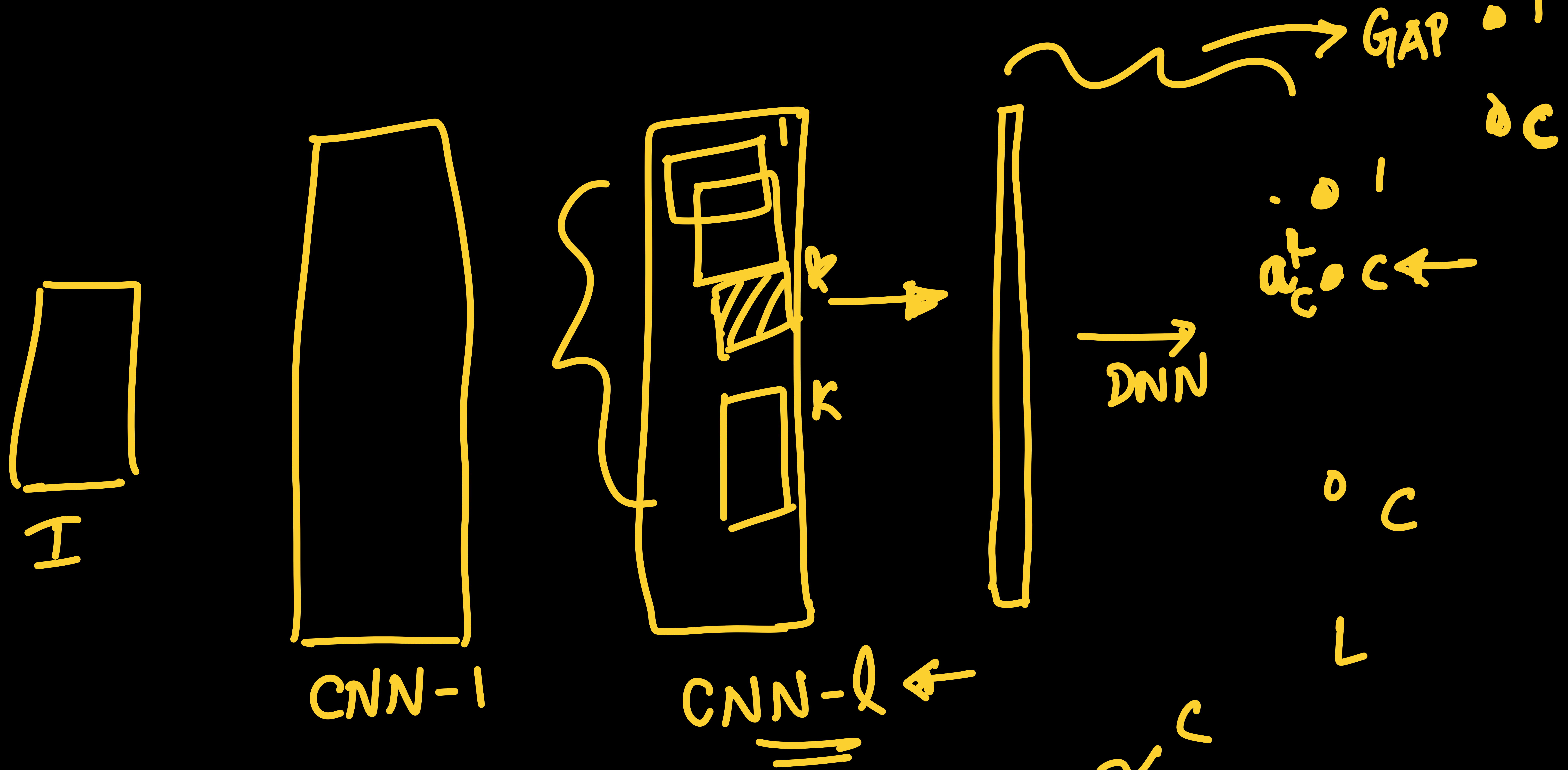
$f^{k,l}(i,j)$

- Assumption - The feature maps from the last convolutional layer capture the spatial information as well as the semantic information required for classification.

- $$S = \sum_{i,j} 1$$

l - last CNN layer

k - feature map index



$$\frac{\partial a_c^L}{\partial f_k^l(i,j)}$$

$$\alpha_k^c$$

Improving CAM without compromising architecture

- Gradient based activation maps (Grad-CAM)

CAM output

$$\mathbf{m}^c = ReLU\Big(\sum_k \alpha_k^c \mathbf{f}^{k,l}(i,j)\Big)$$

Interpolate

- Multiply the gradient based contribution to the individual pixels of the feature maps
- The ReLU operation preserves only the pixels that have a positive influence on the output activations.
  - ➡️ The negative pixels may belong some other class category

Relation between CAM and Grad-CAM

- If the last convolutional layer is followed by a global average pooling (GAP) and softmax layer then, Grad-CAM gives

$$F^{k,L} = \sum_{i,j} \mathbf{f}^{k,L}(i,j)$$

GAP

- The derivative output activation w.r.t GAP output

$$\frac{\partial a^{c,L}}{\partial F^{k,L}} = w_c^{k,L} \qquad \boxed{\frac{\partial a^{c,L}}{\partial \mathbf{f}^{k,L}(i,j)} = w_c^{k,L}}$$

Relation between CAM and Grad-CAM

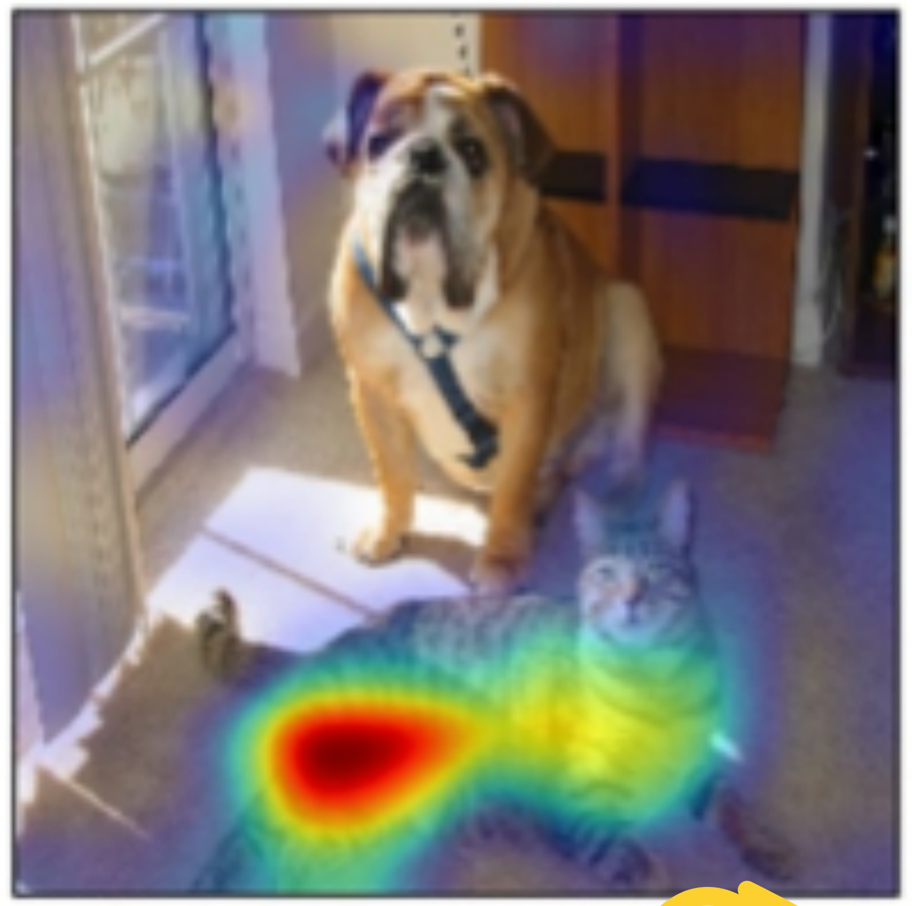
- If the last convolutional layer is followed by a global average pooling (GAP) and softmax layer then, Grad-CAM gives

$$\alpha_k^c = \frac{1}{S}\sum_{i,j}\frac{\partial a^{c,L}}{\partial \mathbf{f}^{k,l}(i,j)} \longrightarrow \alpha_c^k = w_c^{k,L}$$

- Grad-CAM generalizes the CAM framework to neural networks that can have convolutional networks followed by other architectures.

Visualizing Grad-CAM outputs

Tiger-cat



(c) Grad-CAM 'Cat'

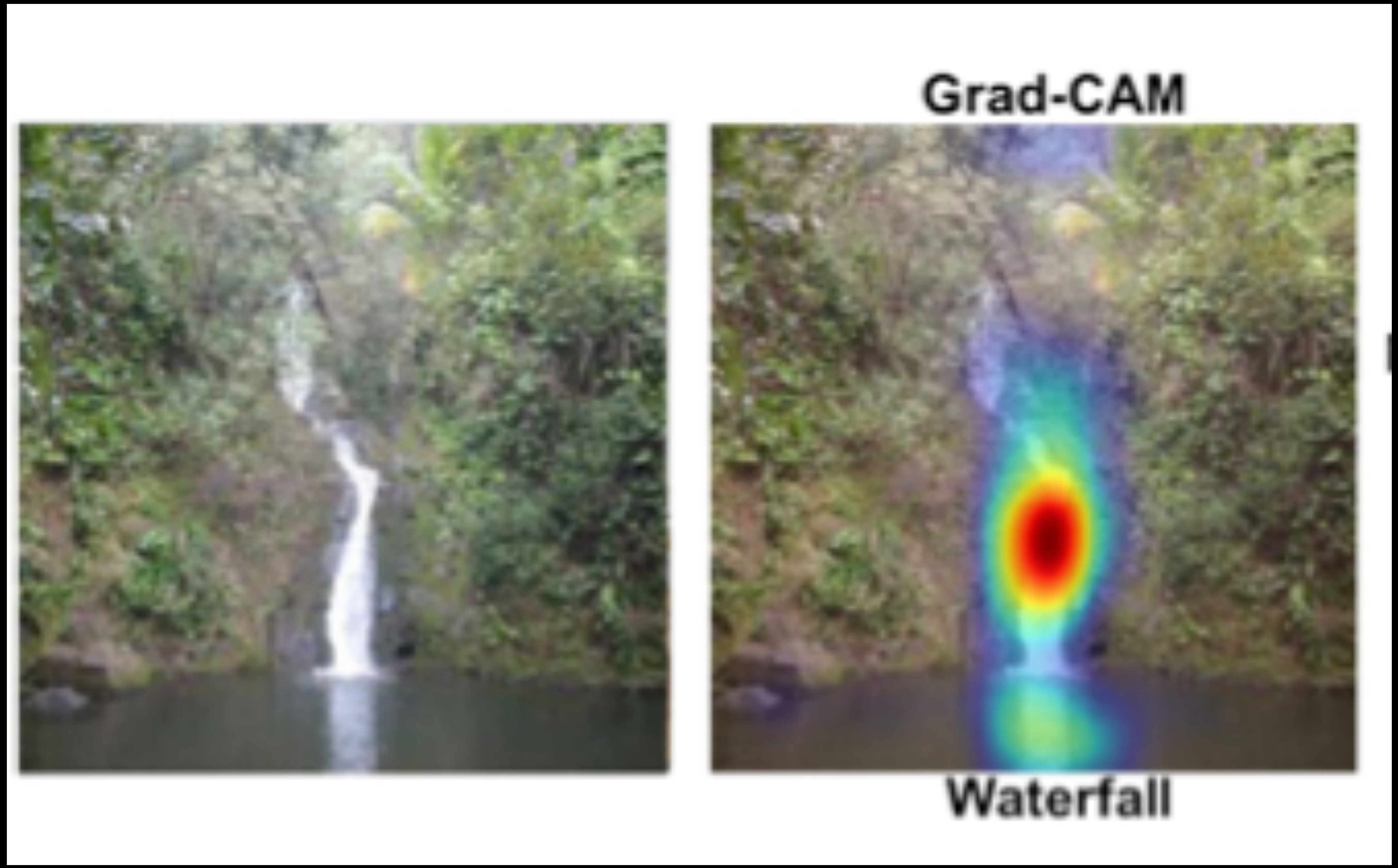
(i) Grad-CAM 'Dog'

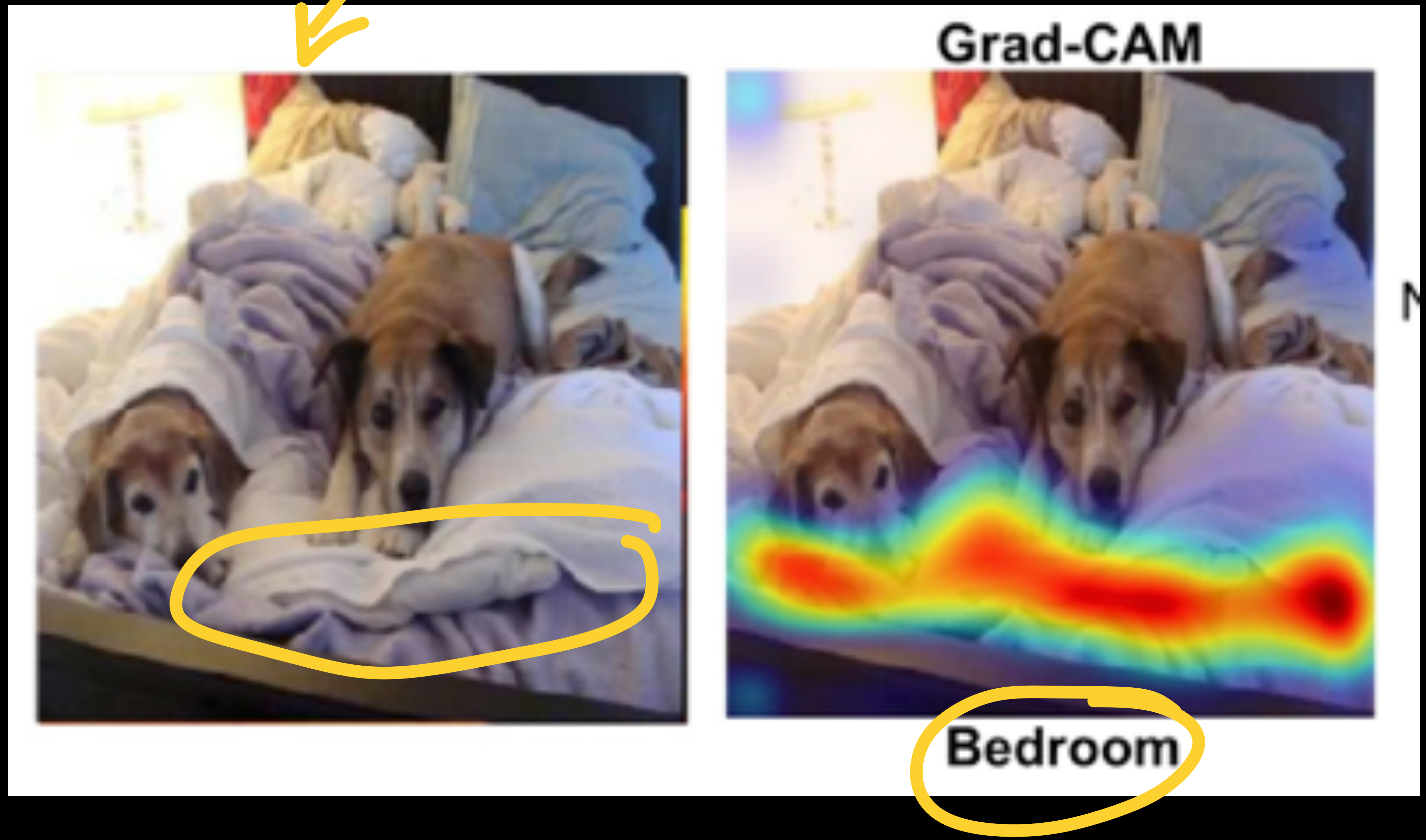
100

101

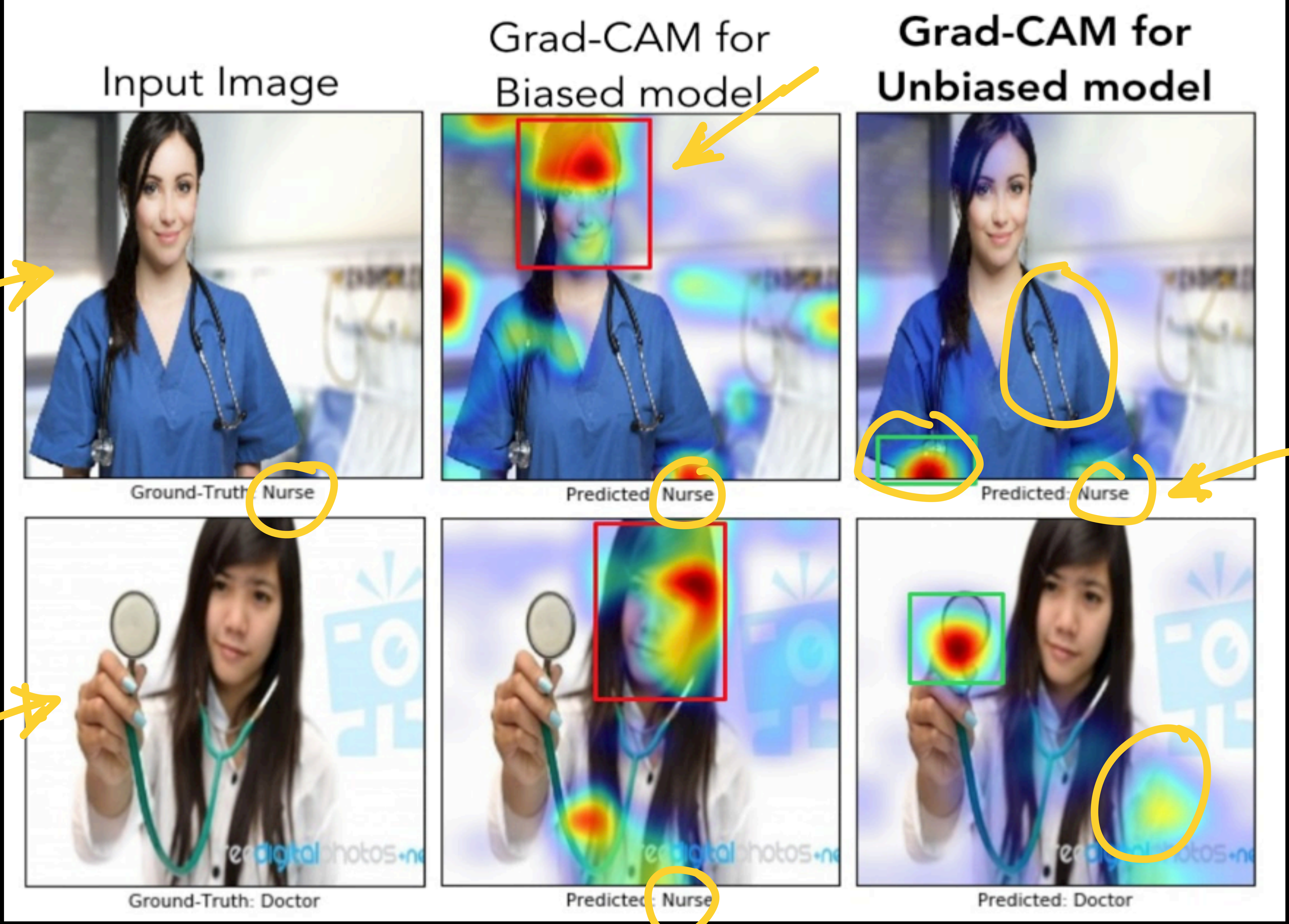
90

Grad-CAM in image captioning



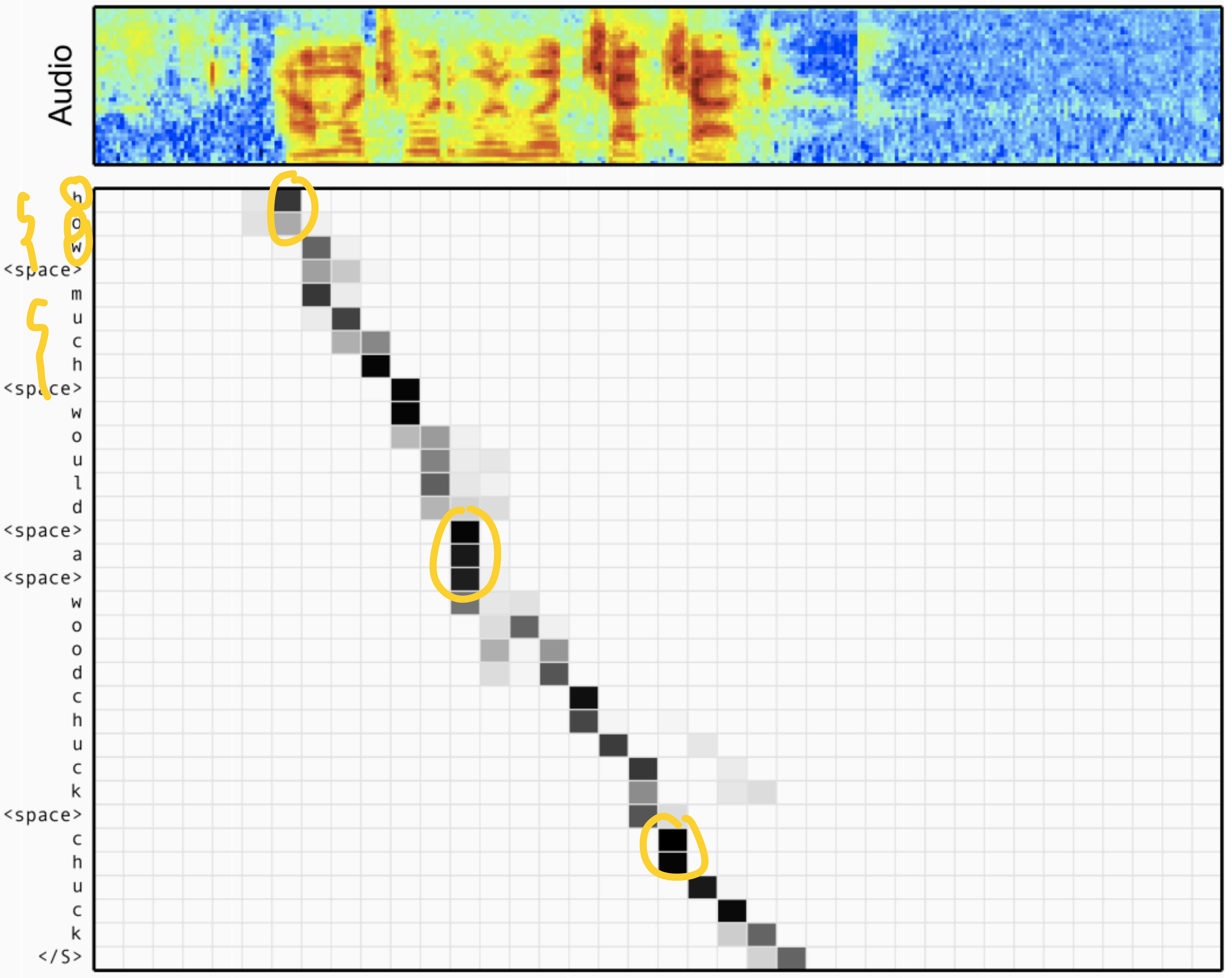


Grad-CAM for identifying model biases



Using attention for visualization

Audio

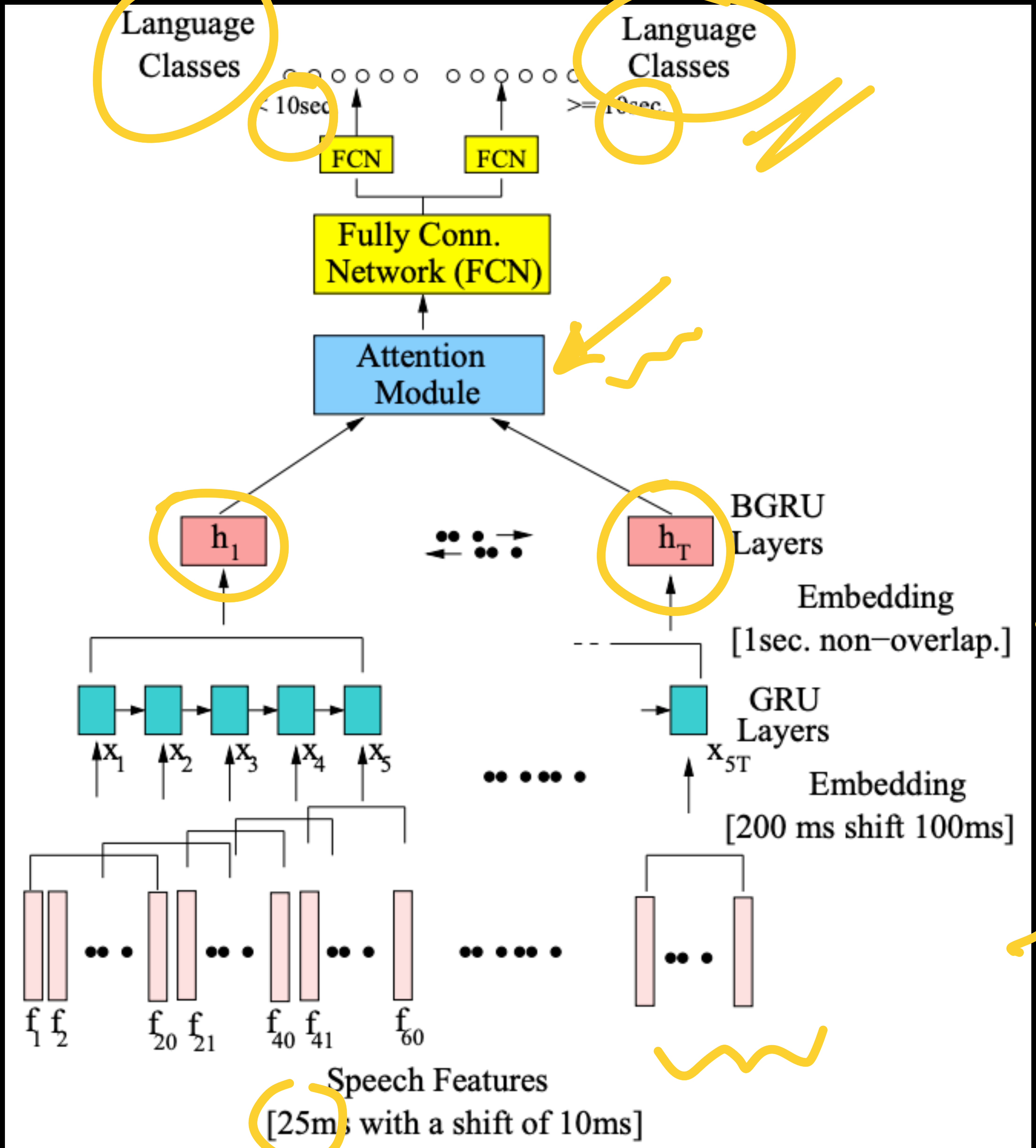


Using attention mechanism for explainability

Towards Relevance and Sequence Modeling in Language Recognition

Bharat Padi, Anand Mohan and Sriram Ganapathy, *Senior Member, IEEE*

Using attention mechanism for explainability



Speech

Eng

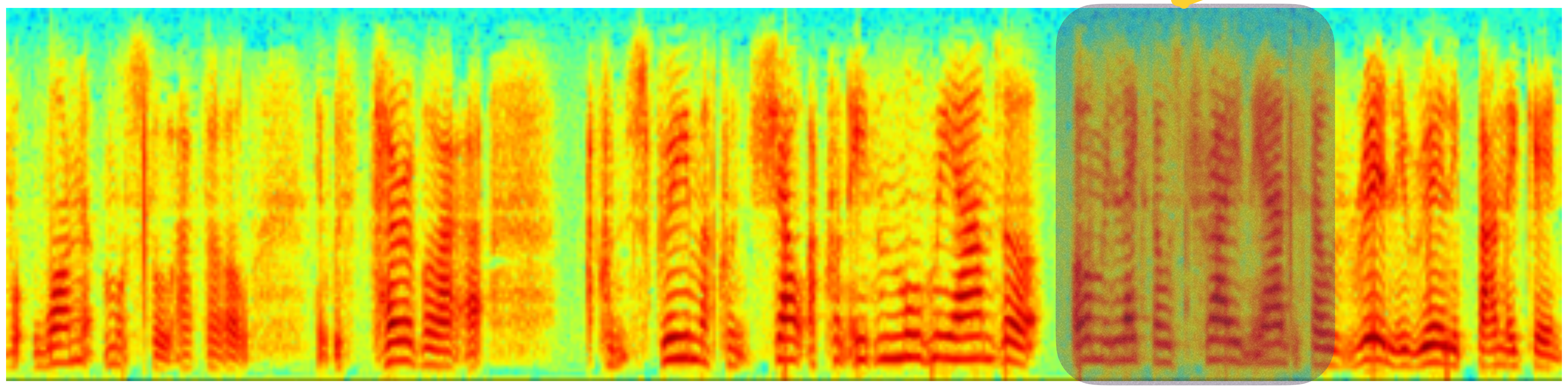
1s

1/5

1/40

Using attention mechanism for explainability

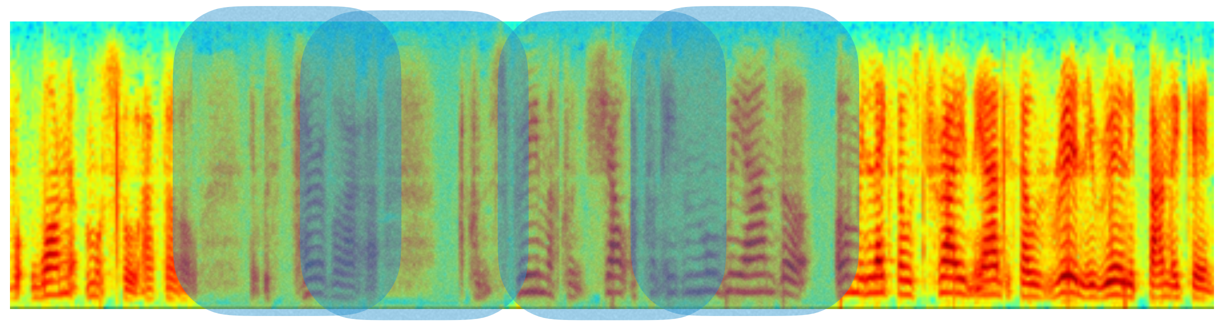
- Certain regions of the audio signal may have more information for the task than the rest.
  - ✓ May also have more signal quality than rest.
  - ✓ For example, language identification involving Eng-UK v/s Eng. US.

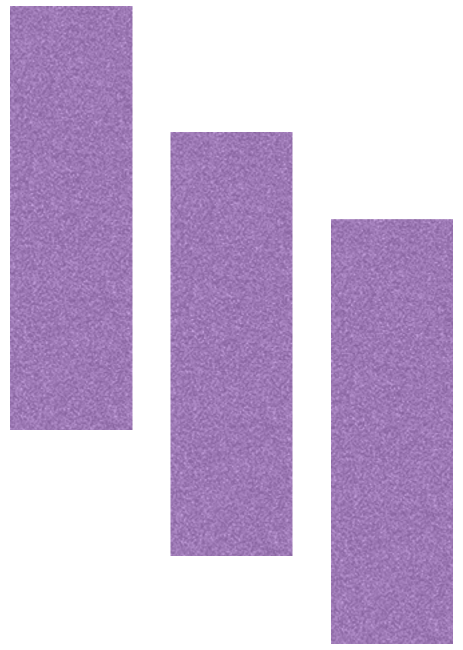


- Current models - use the information from audio with uniformity.

Using attention mechanism for explainability

- Derive short segment i-vectors





Sequence to label model using **attention**

- Attention weighs the importance of each short-term segment feature for the task.

Attention Weight

0-3s

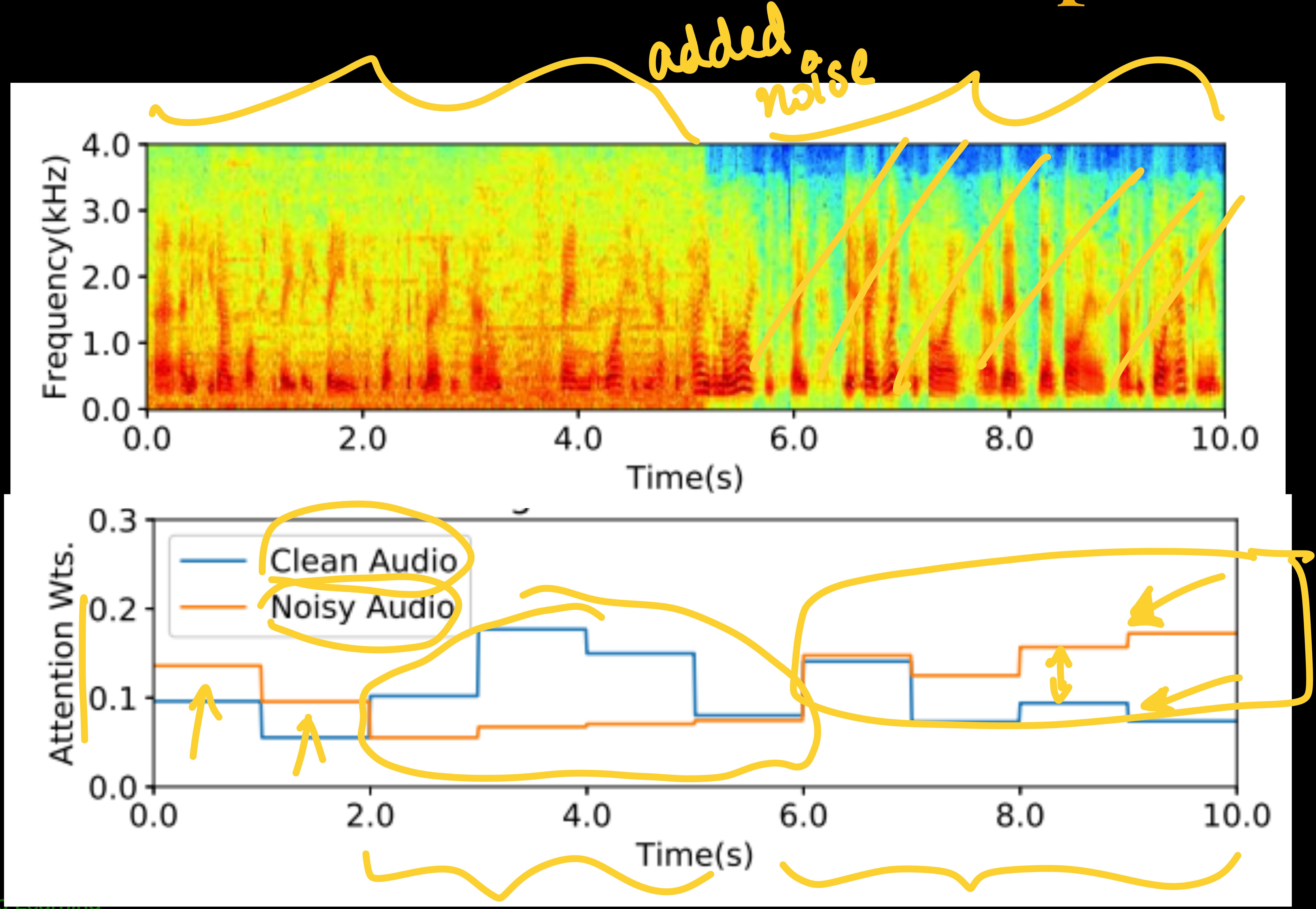
3s-4s

4s - 9s   I couldn't scream, I couldn't shout, I couldn't even move my arms up, or my legs

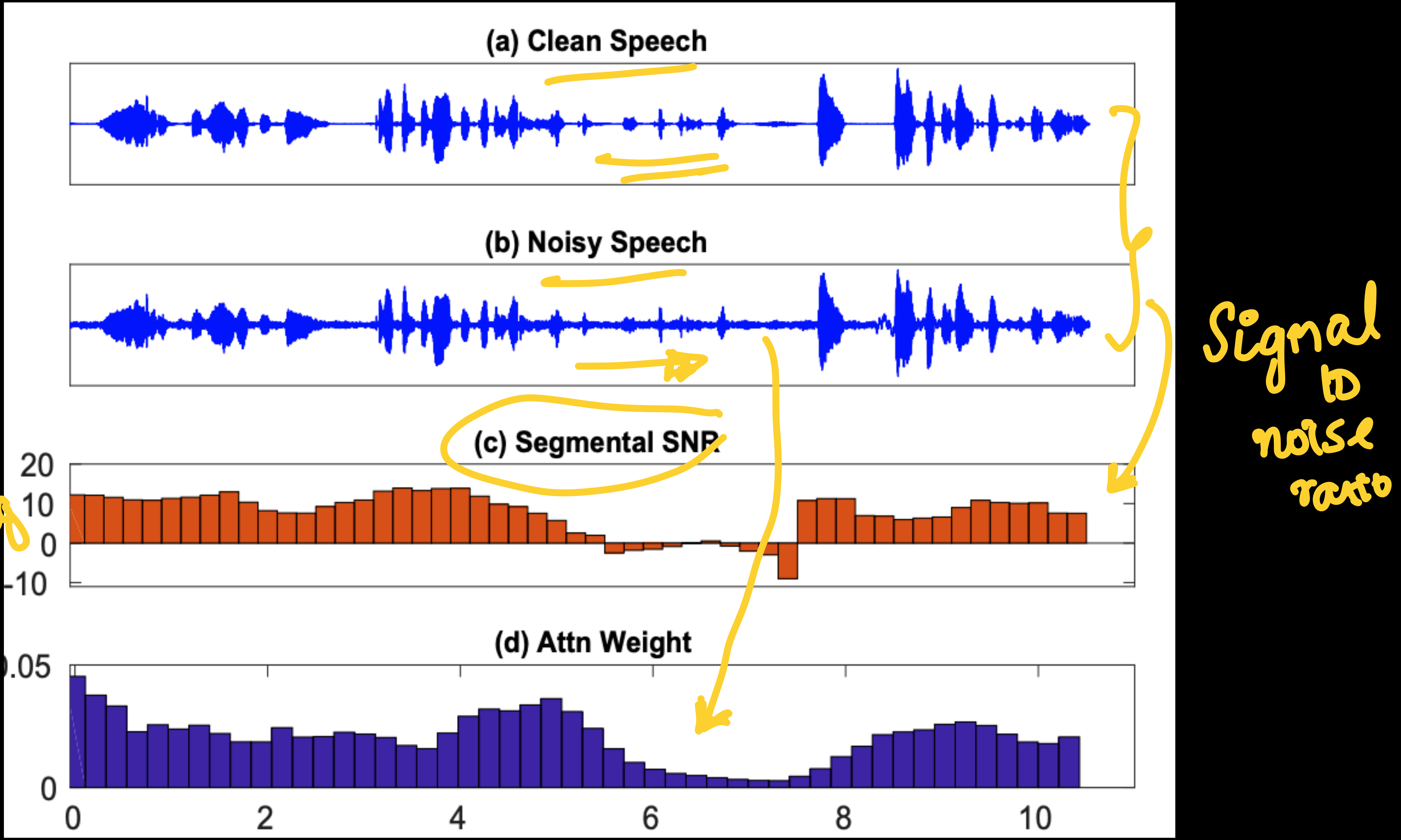
9s -11s

Bharat Padi, et al. 2018 in prep.

Using attention mechanism for explainability



Using attention mechanism for visualization



Summary thus far

- ✴ Analyzing trained neural networks
    - ✓ Hierachical representations
    - ✓ Activation maps to determine saliency
    - ✓ Incorporating attention mechanism for improved explainability