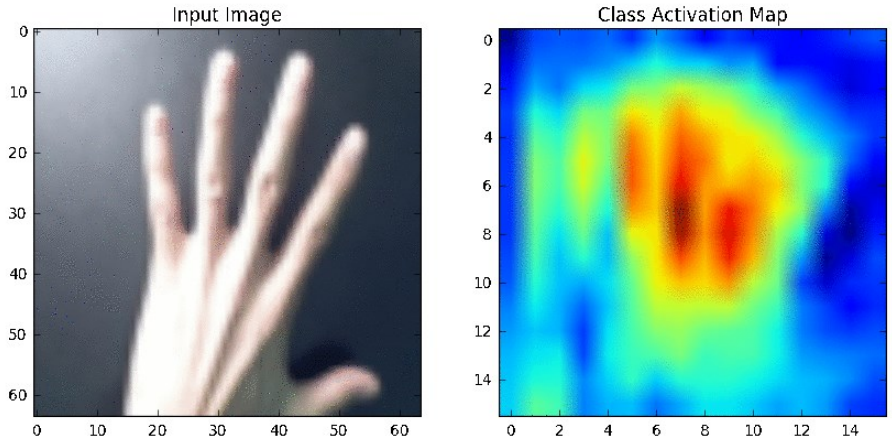
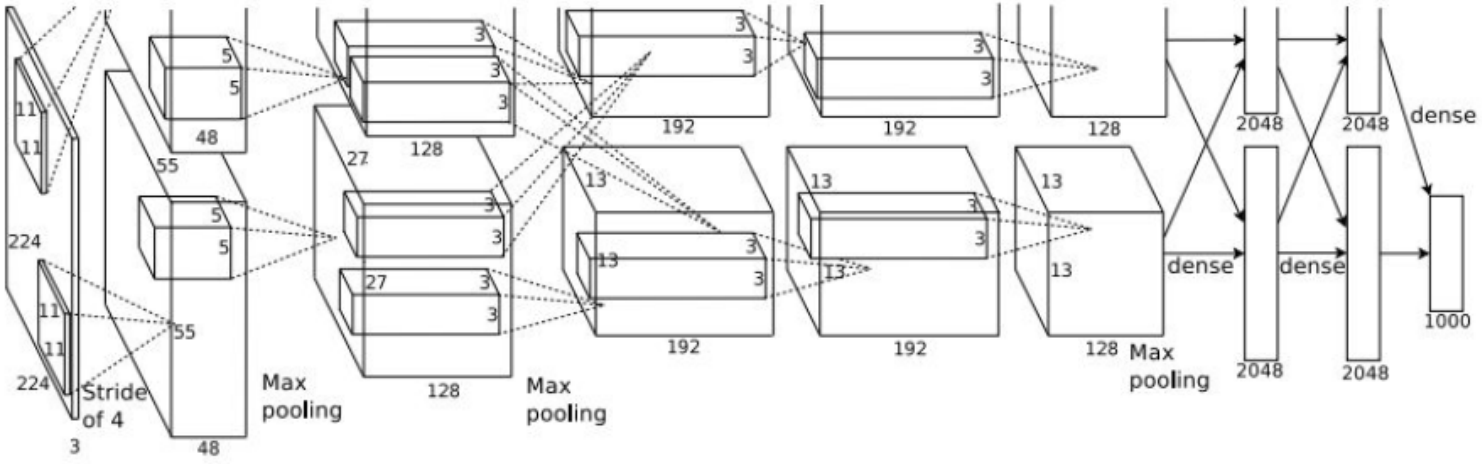
# Visualization of CNN



# What's going on inside CNN?






Class Scores:
1000 numbers

Input Image:
3 x 224 x 224

What are the intermediate features looking for?

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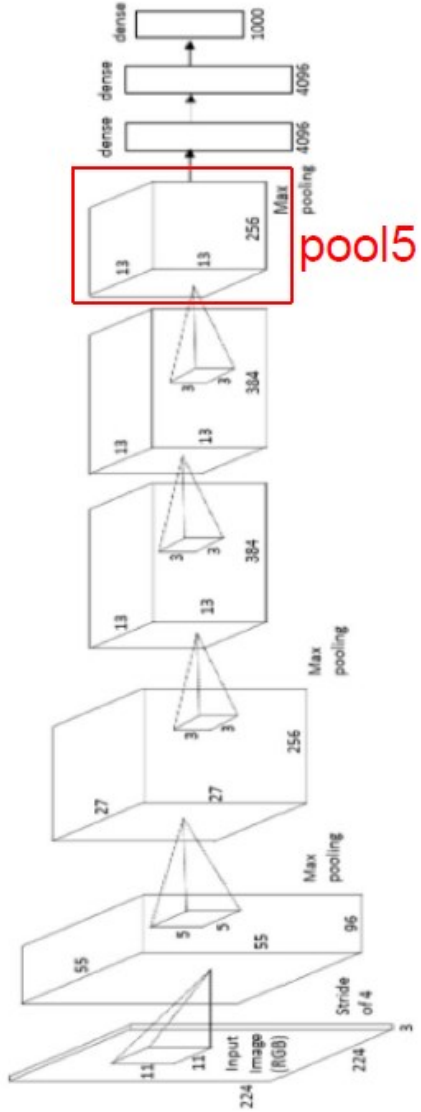
# Visualize Patches that Maximally Activate Neurons

**Figure 4: Top regions for six pool$_5$ units.** Receptive fields and activation values are drawn in white. Some units are aligned to concepts, such as people (row 1) or text (4). Other units capture texture and material properties, such as dot arrays (2) and specular reflections (6).

*Rich feature hierarchies for accurate object detection and semantic segmentation*
*[Girshick, Donahue, Darrell, Malik]*

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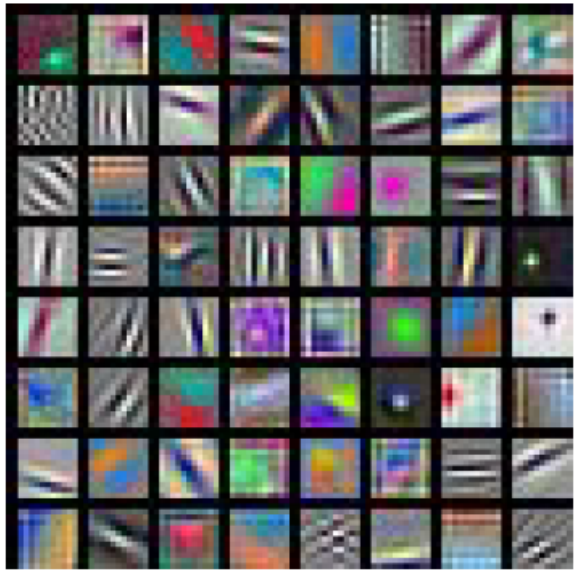
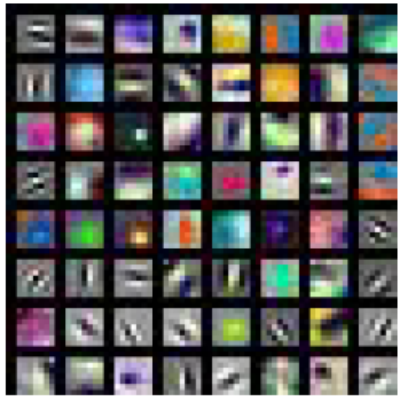
# Visualize Filters

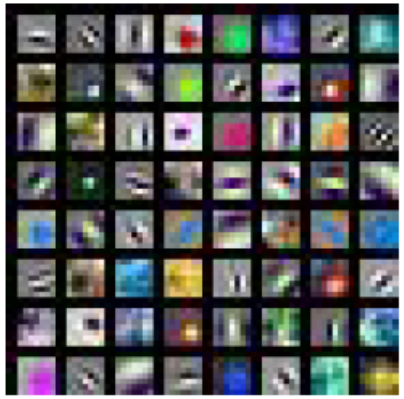
- Only interpretable on the first layer



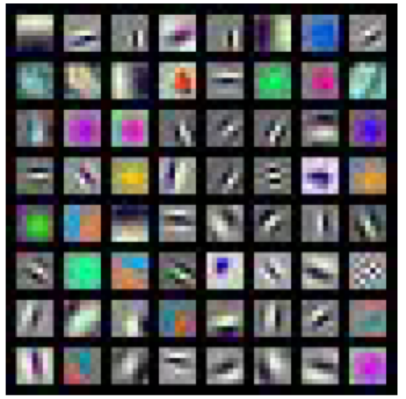
AlexNet:
64 x 3 x 11 x 11



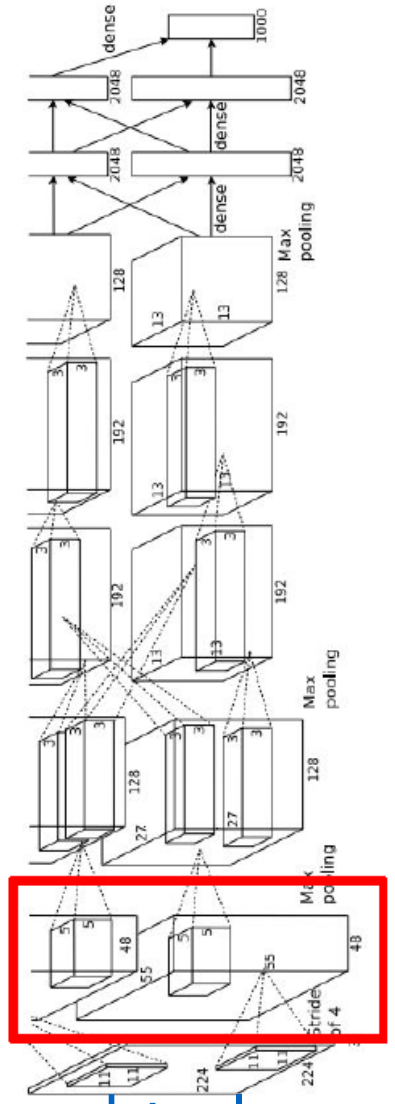
ResNet-18:
64 x 3 x 7 x 7



ResNet-101:
64 x 3 x 7 x 7



DenseNet-121:
64 x 3 x 7 x 7




- http://cs.stanford.edu/people/karpathy/convnetjs/demo/cifar10.html

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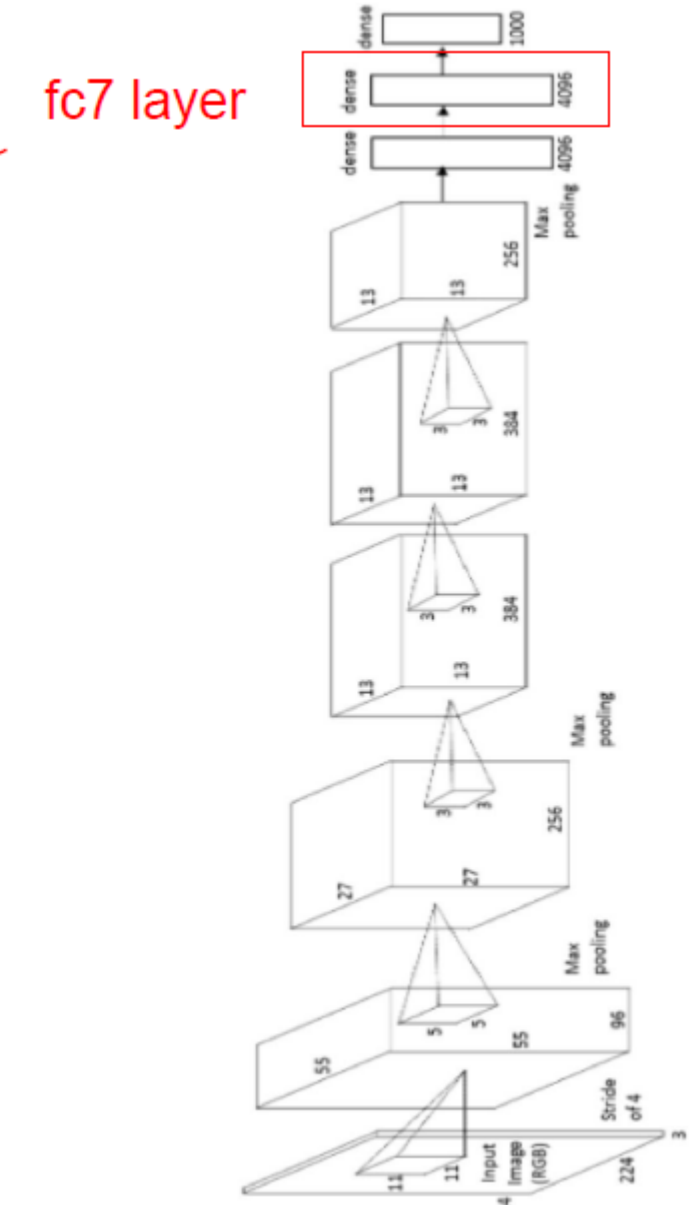
# Visualizing the Representation




4096-dimensional “code” for an image
(layer immediately before the classifier)

can collect the code for many images

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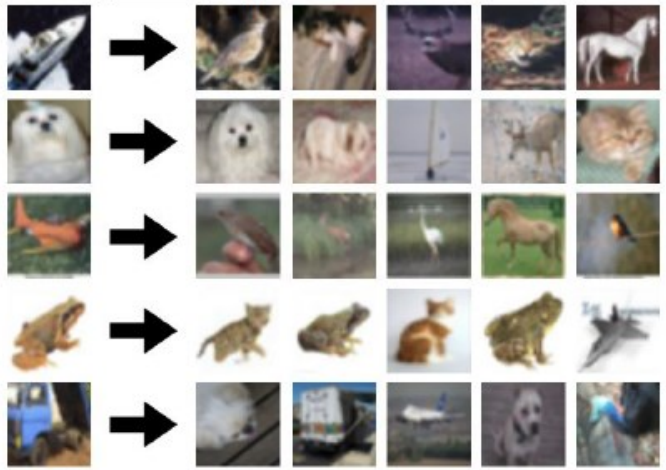
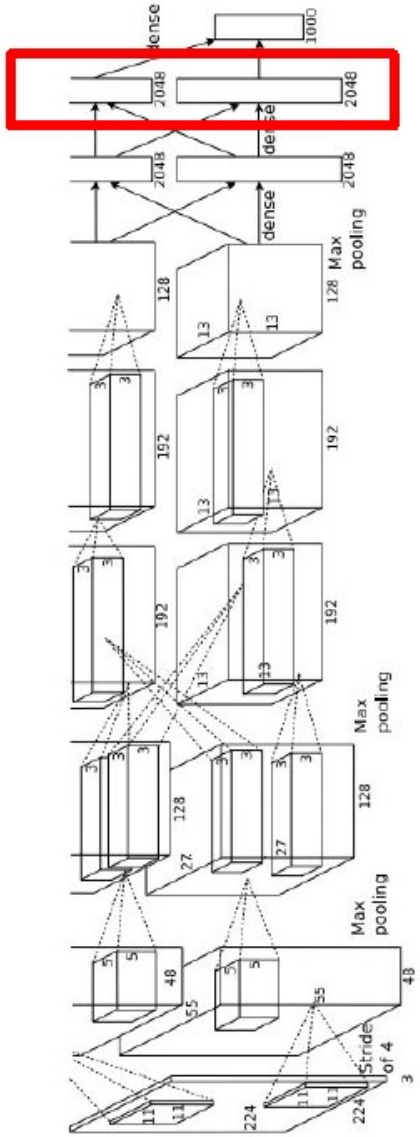
# Last Layer : Nearest Neighbors

**Recall**: Nearest neighbors in pixel space



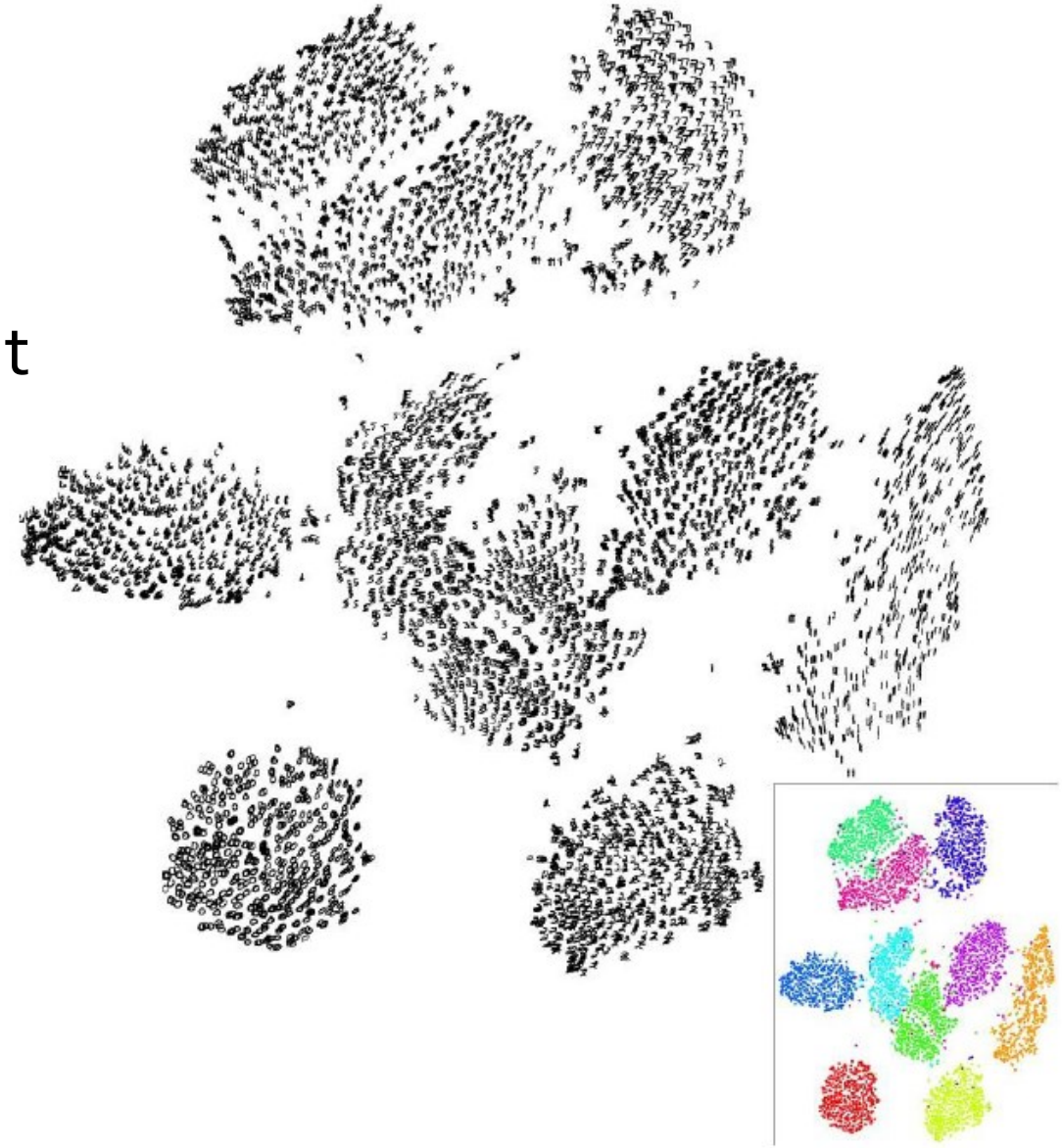
Test image L2 Nearest neighbors in feature space

4096-dim vector

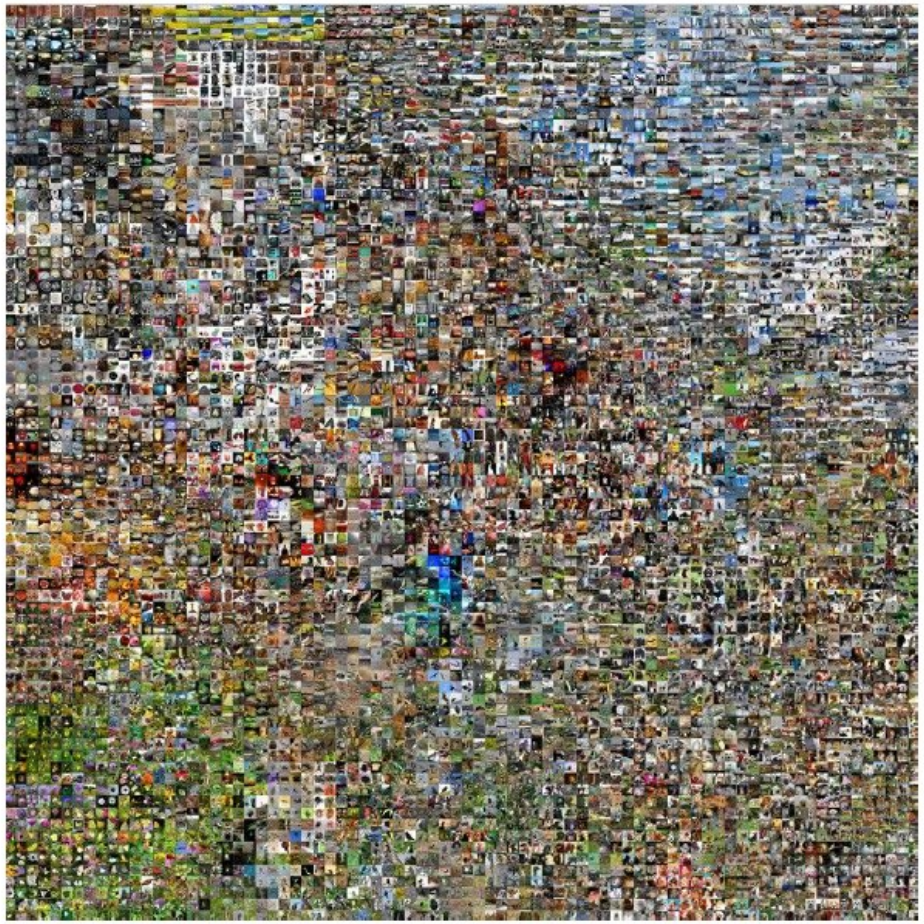


# Last Layer: Dimensionality Reduction

- Visualize the "space" of FC7 feature vectors by reducing dimensionality of vectors from 4096 to 2 dimensions
- Simple algorithm: Principle Component Analysis(PCA)
- More complex: t-SNE



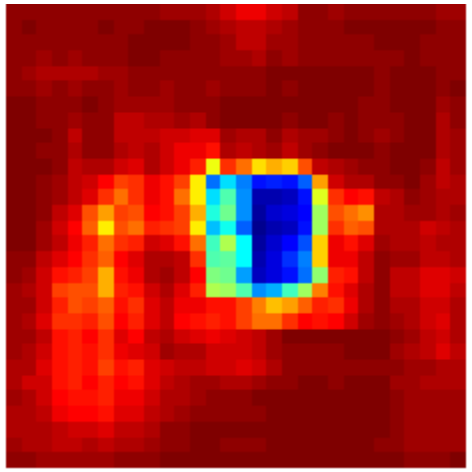
# Last Layer: Dimensionality Reduction

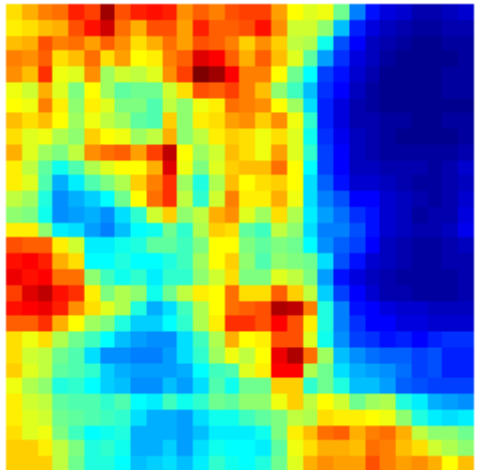


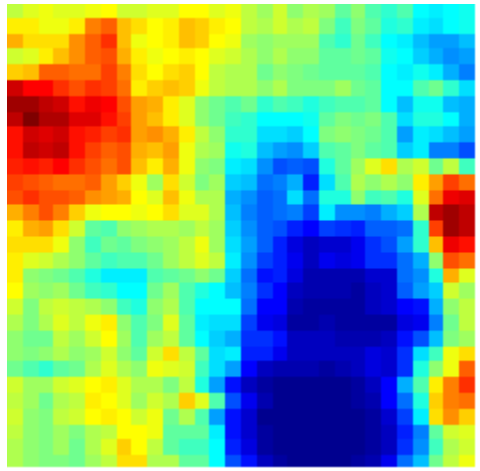
- http://cs.stanford.edu/people/karpathy/cnnembed/

# Occlusion Experiments



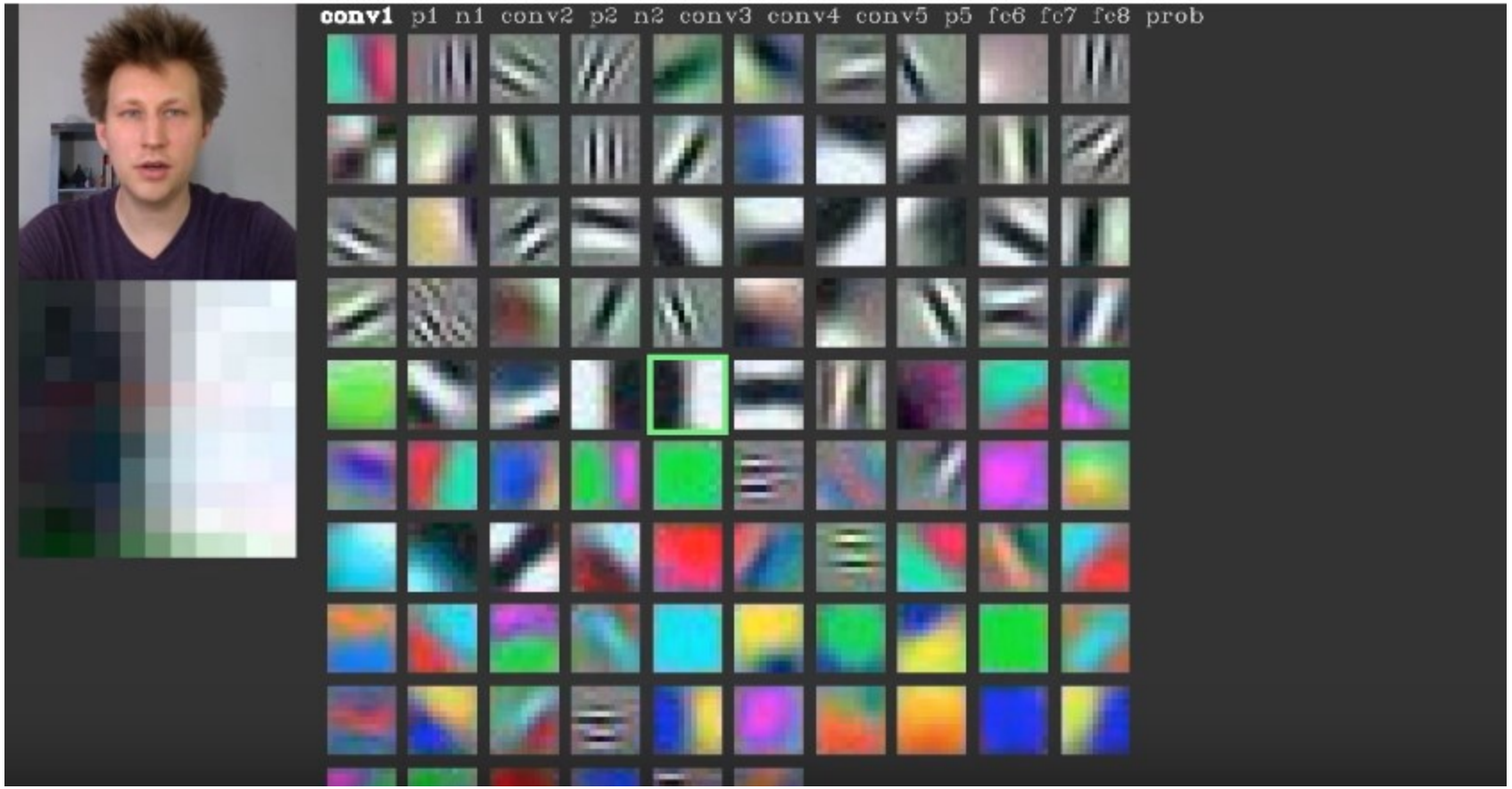





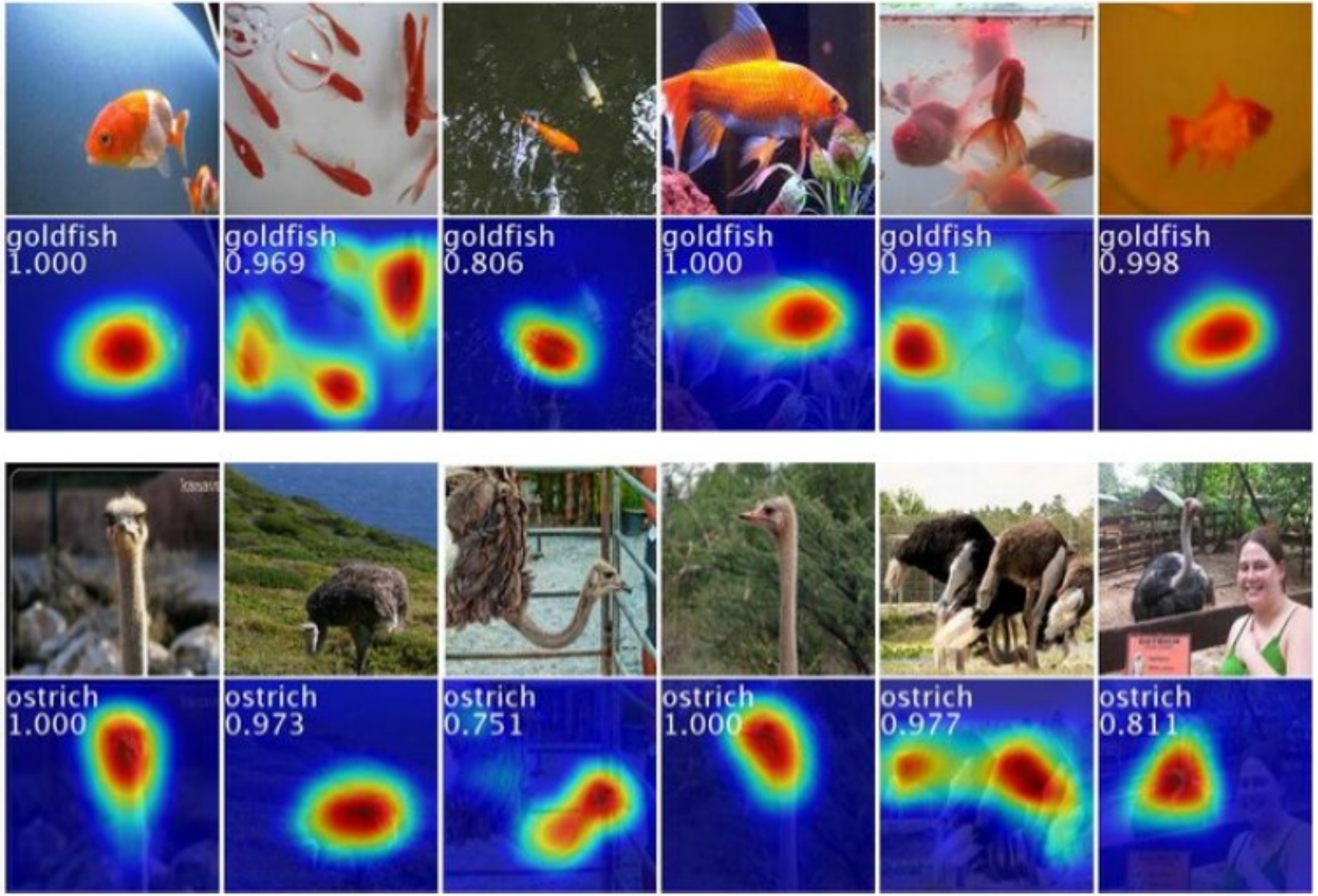


# Visualizing Activations

- https://www.youtube.com/watch?v=AgkfIQ4IGaM



# Weakly Supervised Learning



# Class activation map (CAM)

- **Identify important image regions** by projecting back the weights of output layer to convolutional feature maps.
- CAMs can be generated for each class in single image.
- Regions for each categories are different in given image.
  - palace, dome, church …

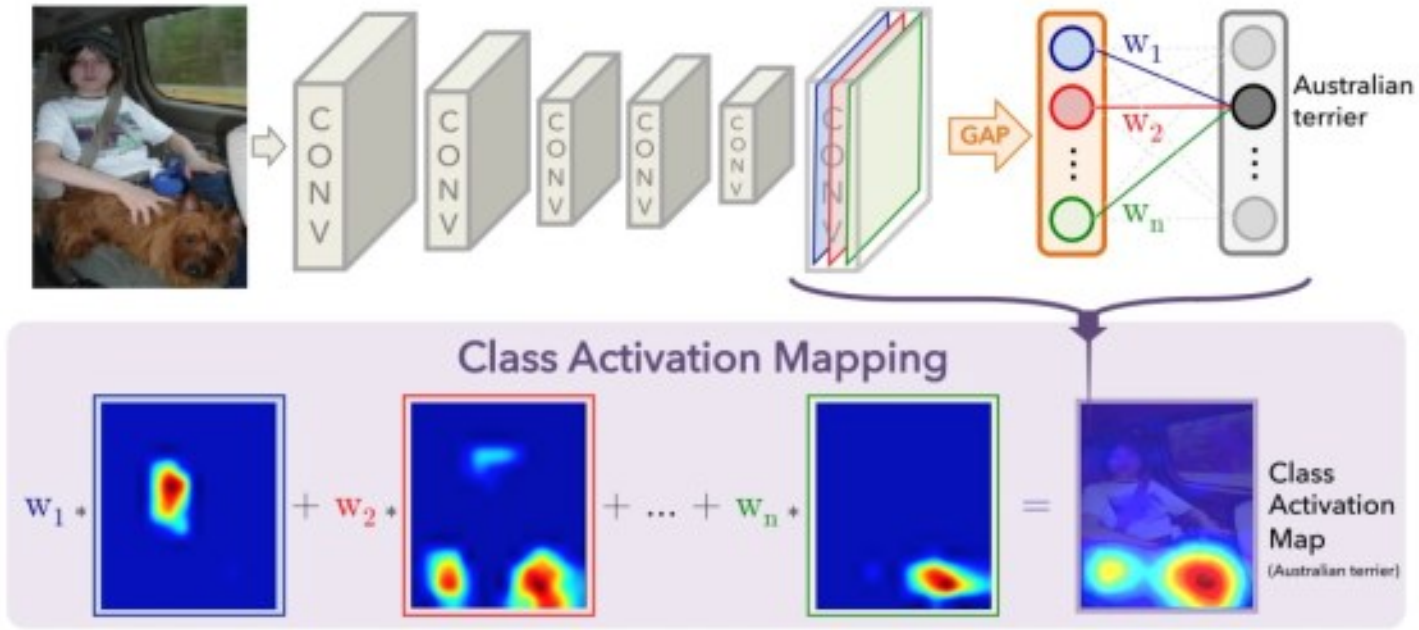



Figure 2. Class Activation Mapping: the predicted class score is mapped back to the previous convolutional layer to generate the class activation maps (CAMs). The CAM highlights the class-specific discriminative regions.

# Results

- CAM on top 5 predictions on an image
- CAM for one object class in images

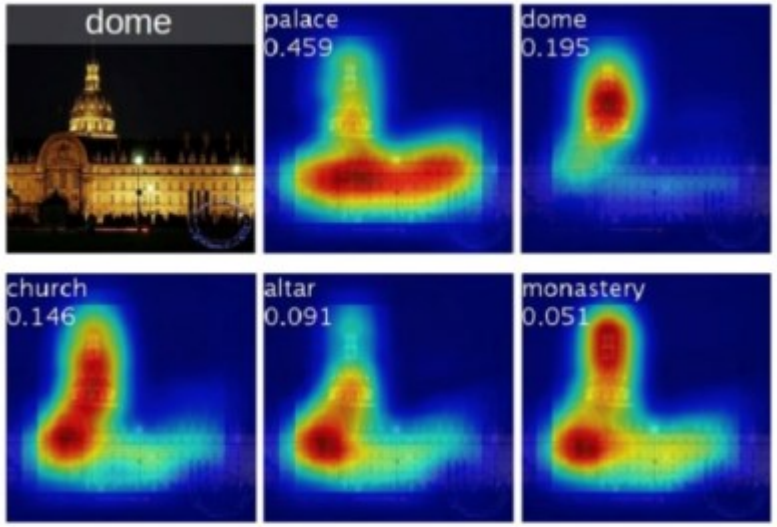



Figure 4. Examples of the CAMs generated from the top 5 predicted categories for the given image with ground-truth as dome. The predicted class and its score are shown above each class activation map. We observe that the highlighted regions vary across predicted classes e.g., *dome* activates the upper round part while *palace* activates the lower flat part of the compound.

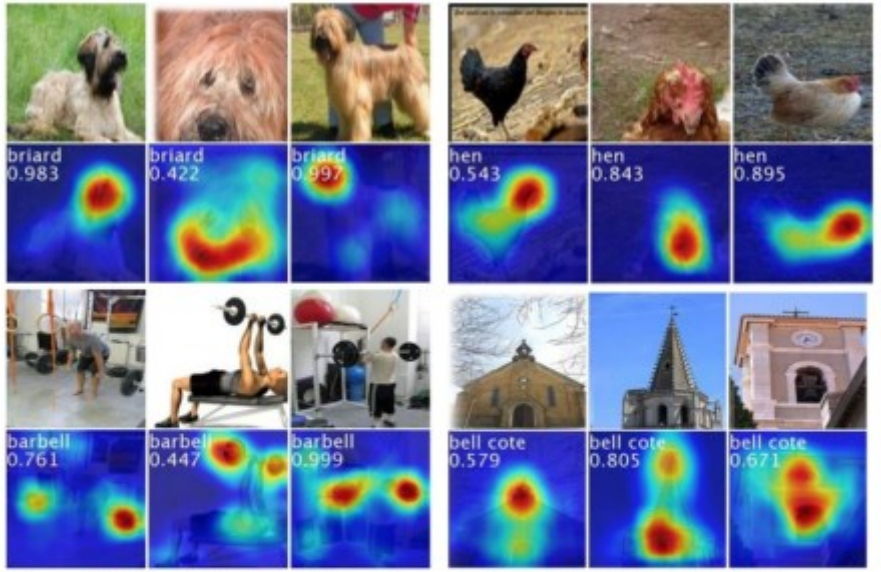
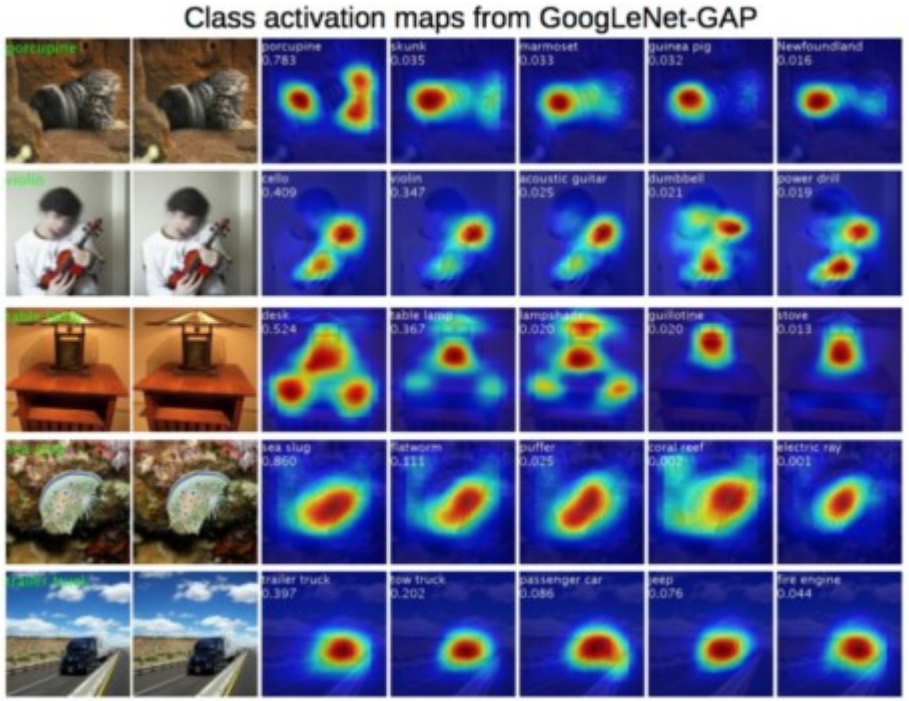



Figure 3. The CAMs of four classes from ILSVRC [20]. The maps highlight the discriminative image regions used for image classification e.g., the head of the animal for *briard* and *hen*, the plates in *barbell*, and the bell in *bell cote*.

# GAP & GMP

- GAP (upper) vs GMP (lower)
- GAP outperforms GMP
- GAP highlights more **complete** object regions and less background noise.
- Loss for average pooling benefits when the network identifies ***all* discriminative** regions of an object



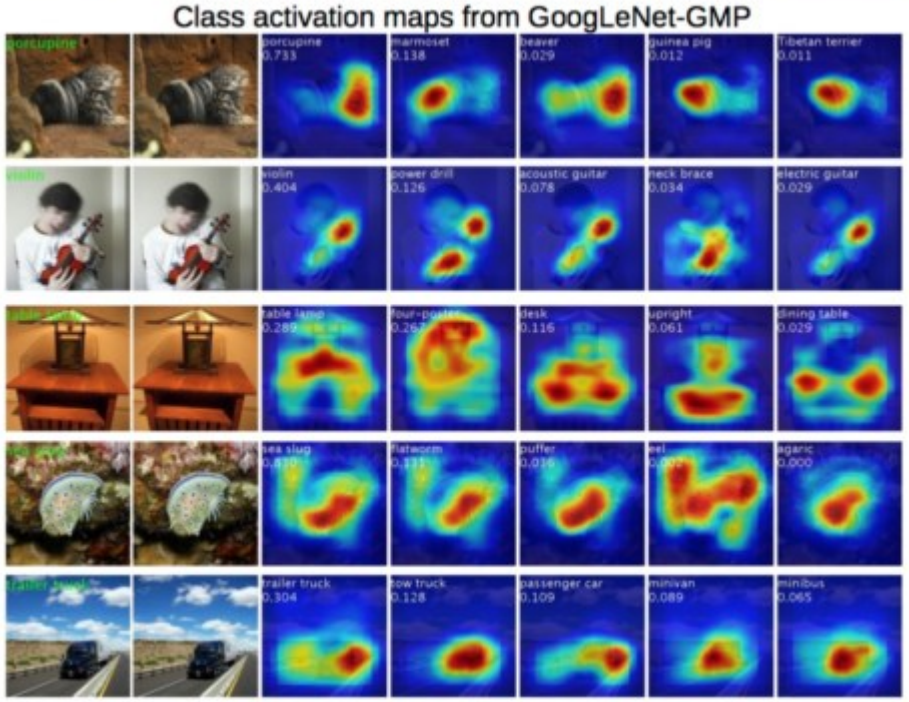




Table 1. Classification error on the ILSVRC validation

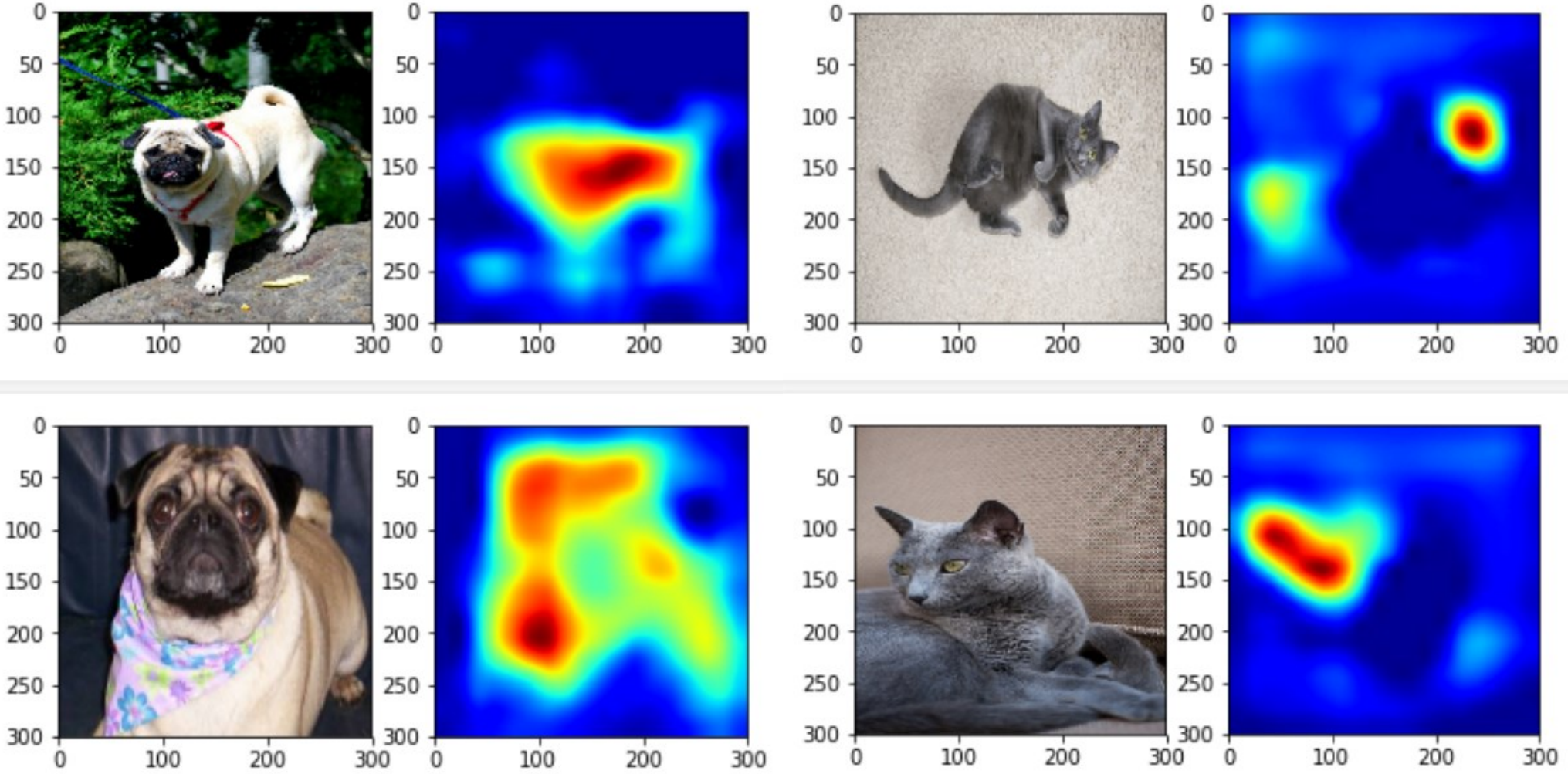
| Networks | top-1 val. error | top-5 val. error |
|---|---|---|
| VGGnet-GAP | 33.4 | 12.2 |
| GoogLeNet-GAP | 35.0 | 13.2 |
| AlexNet*-GAP | 44.9 | 20.9 |
| AlexNet-GAP | 51.1 | 26.3 |
| GoogLeNet | 31.9 | 11.3 |
| VGGnet | 31.2 | 11.4 |
| AlexNet | 42.6 | 19.5 |
| NIN | 41.9 | 19.6 |
| GoogLeNet-GMP | 35.6 | 13.9 |

Table 2. Localization error on the ILSVRC validation set. *Backprop* refers to using [22] for localization instead of CAM.

| Method | top-1 val.error | top-5 val. error |
|---|---|---|
| GoogLeNet-GAP | **56.40** | **43.00** |
| VGGnet-GAP | 57.20 | 45.14 |
| GoogLeNet | 60.09 | 49.34 |
| AlexNet*-GAP | 63.75 | 49.53 |
| AlexNet-GAP | 67.19 | 52.16 |
| NIN | 65.47 | 54.19 |
| Backprop on GoogLeNet | 61.31 | 50.55 |
| Backprop on VGGnet | 61.12 | 51.46 |
| Backprop on AlexNet | 65.17 | 52.64 |
| GoogLeNet-GMP | 57.78 | 45.26 |

# Weakness of CAM (Weakly Supervised Localicztion)

- Focusing on discriminative features



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