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# Deep Learning Applications for Computer Vision

Lecture 18: Visualizing CNNs



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# Visualizing the CNNs

w, b

- What are the parameters the model has learned?
  - What do the filters look like?



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# Visualizing the CNNs

- What are the parameters the model has learned?
  - What do the filters look like?
- What features did the model learn?
  - Edges, blobs, corners, ... , eyes, fur, ...



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# Visualizing the CNNs

- What are the parameters the model has learned?
  - What do the filters look like?
- What features did the model learn?
  - Edges, blobs, corners, ... , eyes, fur, ...
- How does the model decide the category for a new image?
  - What do activation maps look like?
  - Which pixels in an image carry more “weight” in the classification decision?

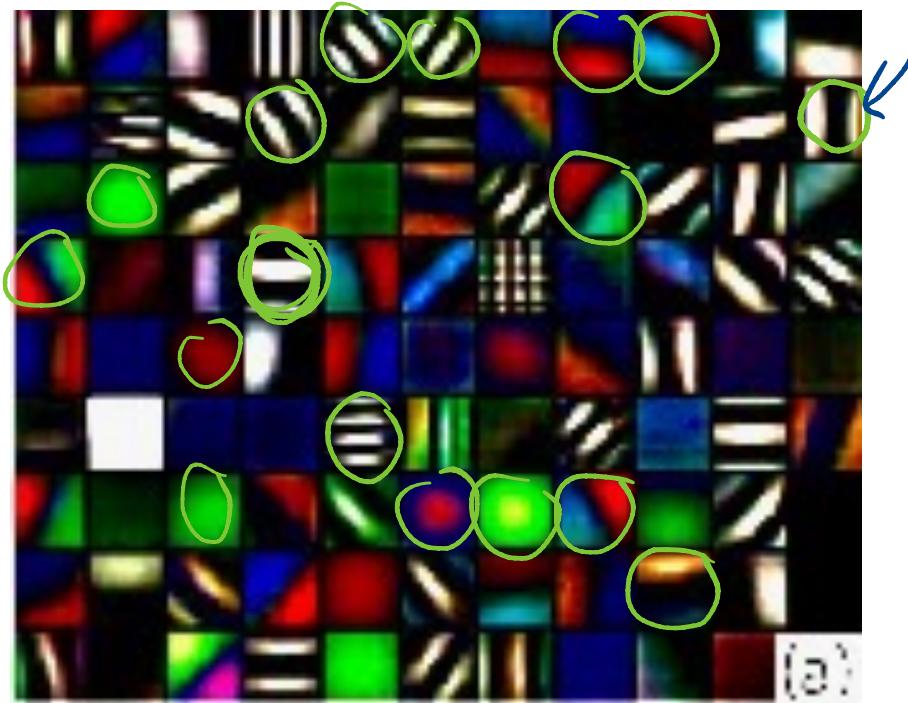
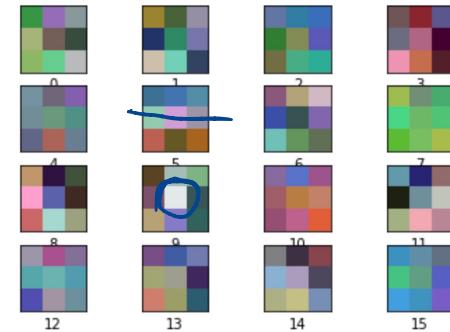


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# Visualizing the filters

$3 \times 3 \times 3$

- For first convolutional layer
- AlexNet first layer:
  - 64 filters of size  $11 \times 11 \times 3$



- edges - oriented  
- blobs  
- opposing colors

Figure 6 a) from Zeiler and Fergus, "Visualizing and Understanding Convolutional Networks", ECCV 2014



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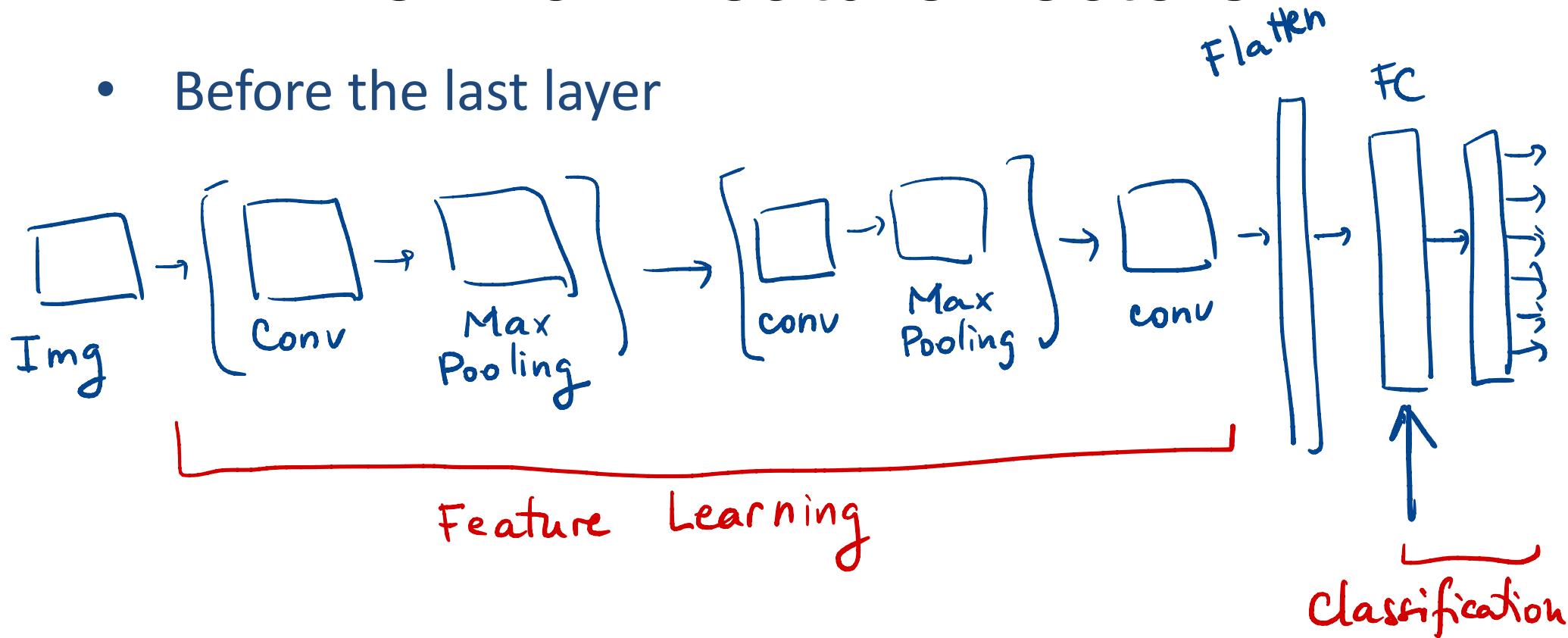
# Visualizing the filters

- For second convolutional layer
  - does not have the shape of an image  
(in our last tutorial second layer: 32 filters of size  $3 \times 3 \times 32$ )
- We could visualize  $32 * 32$  greyscale images of size  $3 \times 3 \dots$
- The input into the second conv layer is not an image ...  
*Difficult to interpret*



# The final “Feature vectors”

- Before the last layer



# The final “Feature vectors”

- Before the last layer
- Flatten to 1024, 4096 column vector



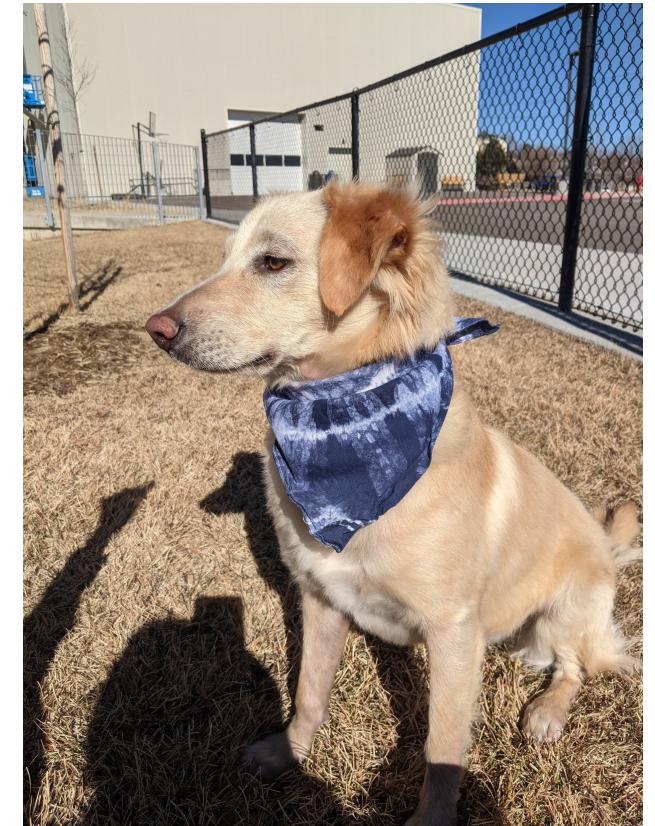
*Clustering : use distance metric*



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# Nearest neighbor clustering

- Semantic clustering: images that are different in pixel intensities cluster together in feature space



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# Classification decisions

- What pixels influence the classification decision most?
- Is the model truly identifying the object, or using surrounding data

## Occlusion Sensitivity

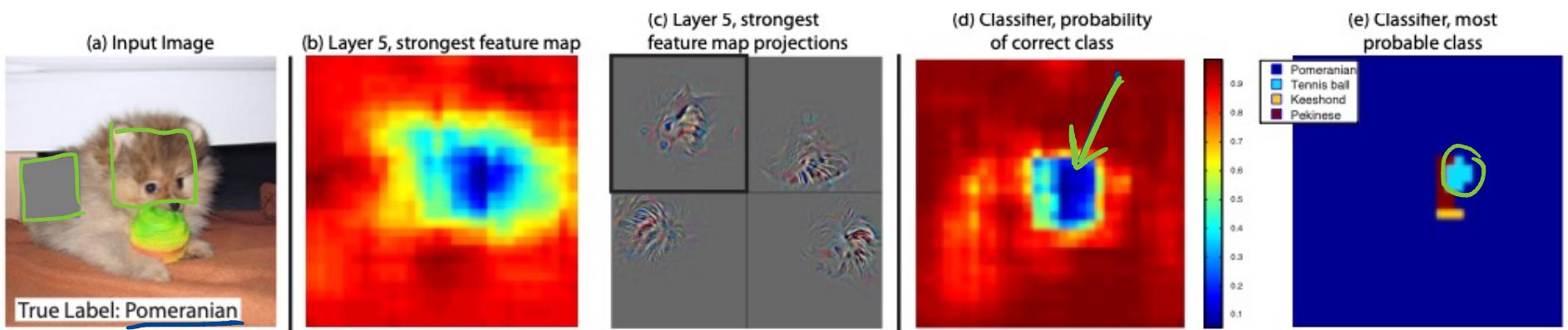


Figure 7 (first row) from Zeiler and Fergus, “Visualizing and Understanding Convolutional Networks”, ECCV 2014

95 %



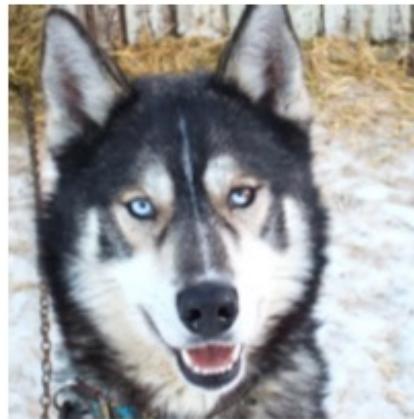
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# Occlusion Sensitivity

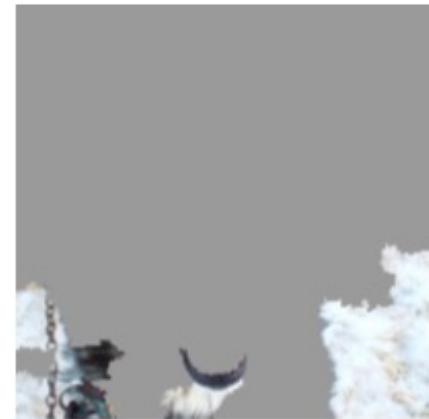
- Bad data example:

Husky vs Wolf

! All wolf pictures  
had snow



(a) Husky classified as wolf



(b) Explanation

Figure 11: Raw data and explanation of a bad model's prediction in the "Husky vs Wolf" task.

	Before	After
Trusted the bad model	10 out of 27	3 out of 27
Snow as a potential feature	12 out of 27	25 out of 27

Table 2: "Husky vs Wolf" experiment results.

Figure 11 and Table 2 from Marco Tulio Ribeiro, Sameer Singh, Carlos Guestrin - "Why Should I Trust You?": Explaining the Predictions of Any Classifier, 2016



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