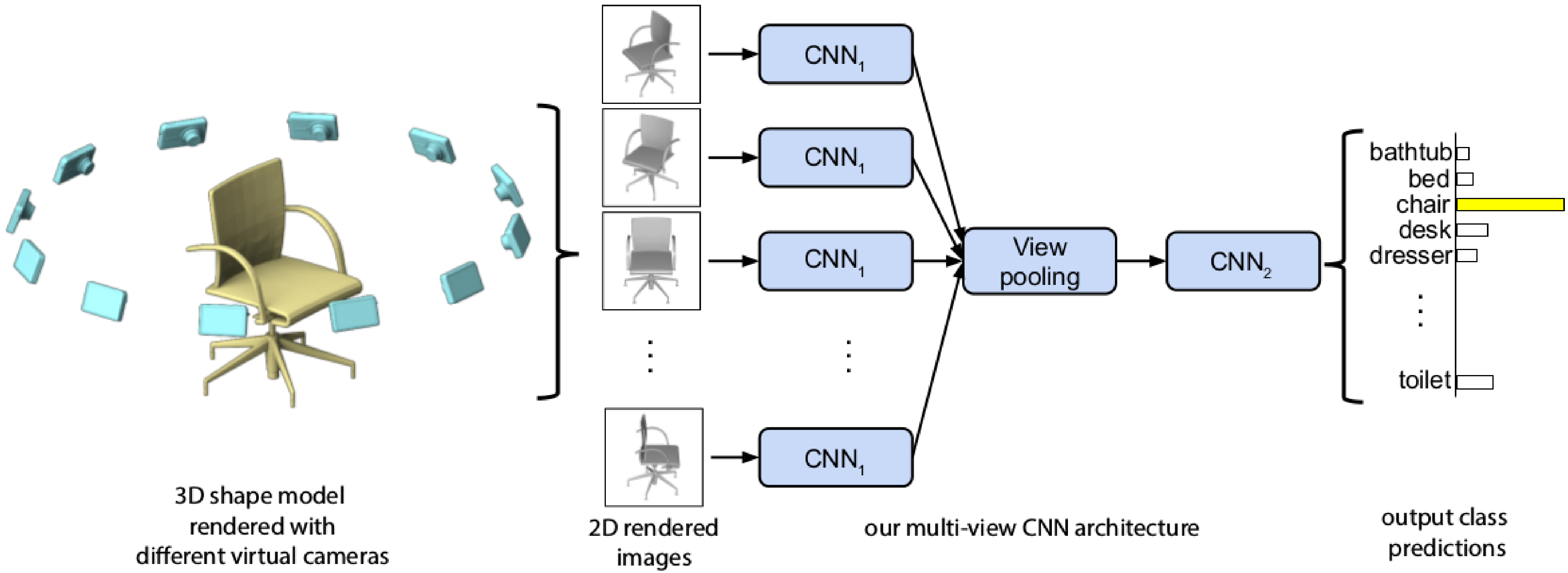
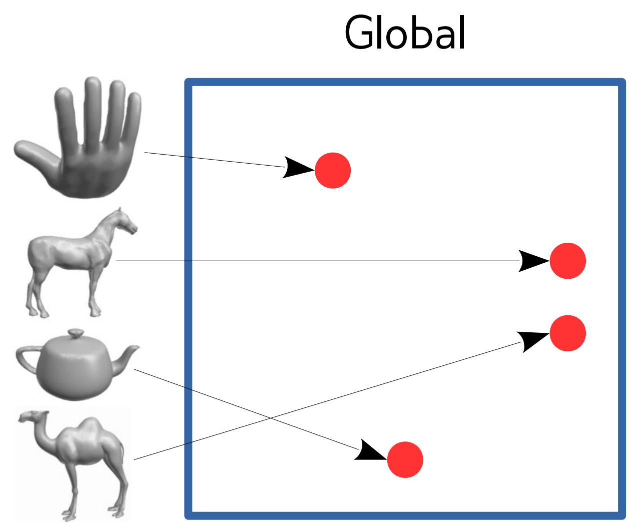


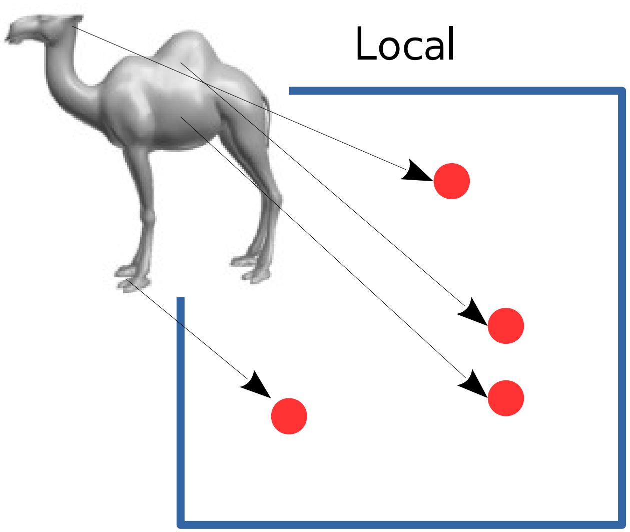
Shape Descriptors - III

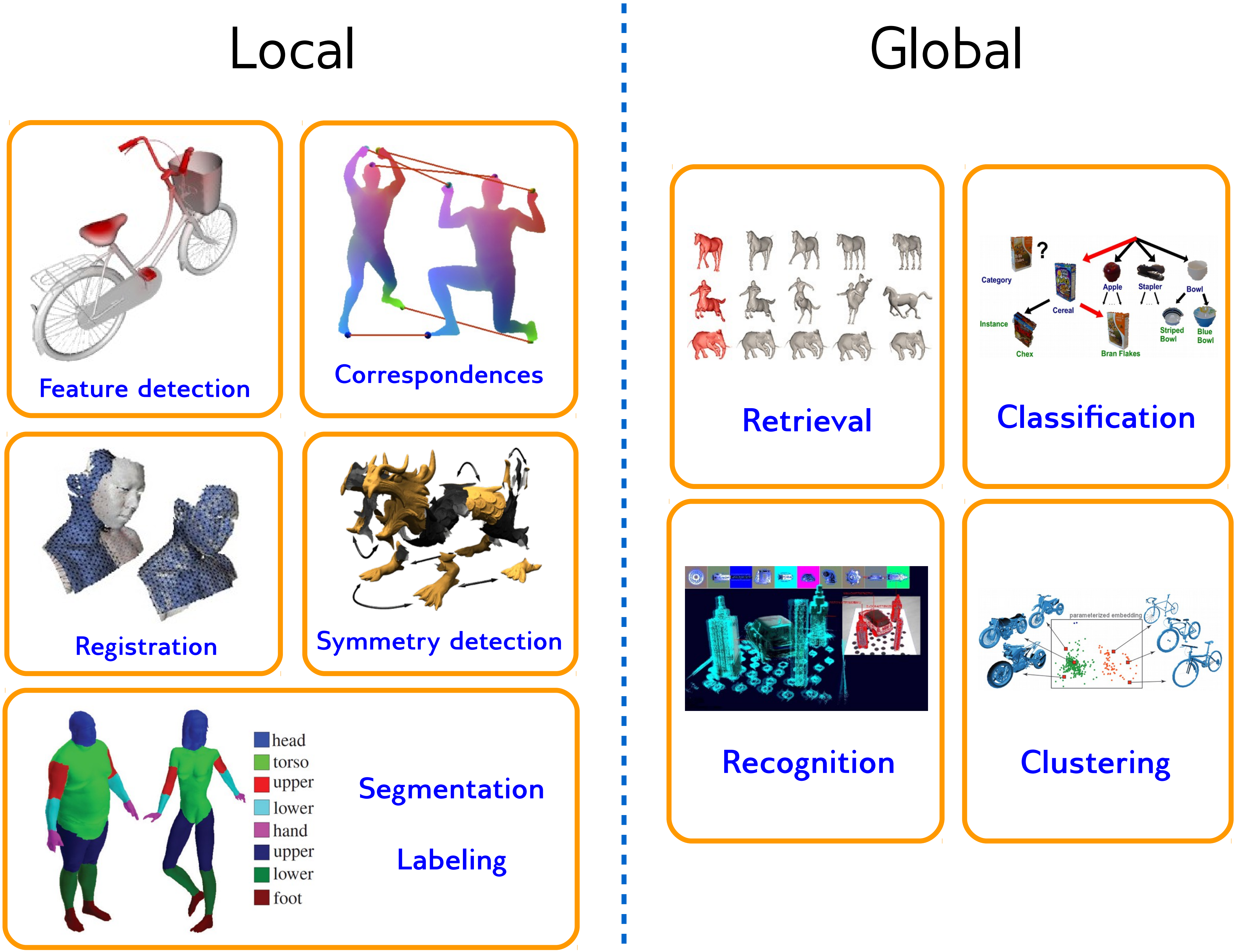
Siddhartha Chaudhuri http://www.cse.iitb.ac.in/~cs749

Recap

- A **shape descriptor** is a set of numbers that describes a shape in a way that is
  - Concise
  - Quick to compute
  - Efficient to compare
  - Discriminative
- **Local descriptors** describe (neighborhoods around) points
- **Global descriptors** describe whole objects
- Typically, the descriptors form a vector space with a meaningful distance metric







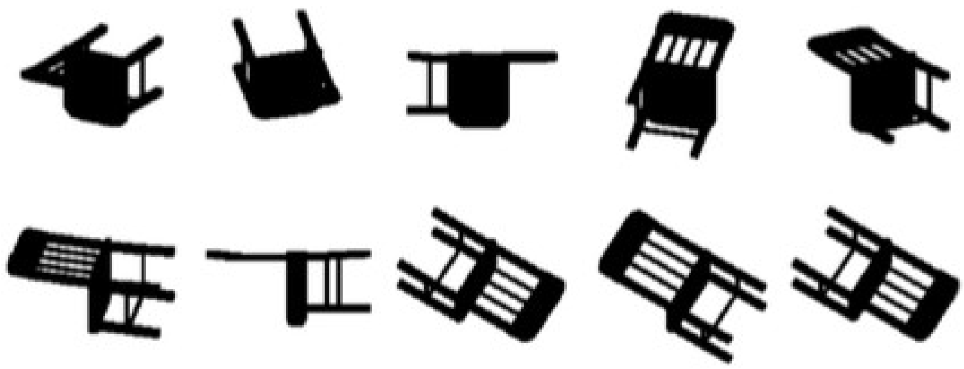
Local
Global
Feature detection
Correspondences
Registration
Symmetry detection
head
torso
upper
lower
hand
upper
lower
foot
Segmentation
Labeling
Retrieval
?
Category
Apple
Stapler
Bowl
Cereal
Instance
Striped Bowl
Blue Bowl
Chex
Bran Flakes
Classification
Recognition
parameterized embedding
Clustering

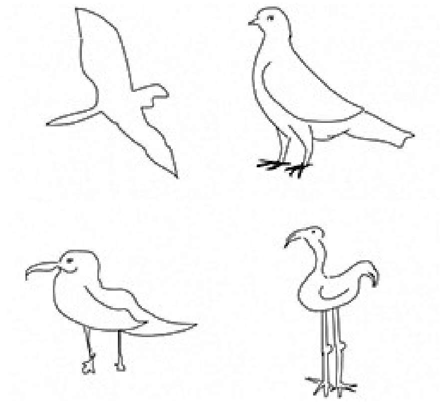
Today

- 2D global descriptors for 3D shapes
  - Light Field Descriptor (LFD)
  - Multi-View Convolutional Neural Network (MVCNN)

Why 2D?

- 2D views contain a lot of information about a shape
  - That's how humans see stuff, and we do quite well

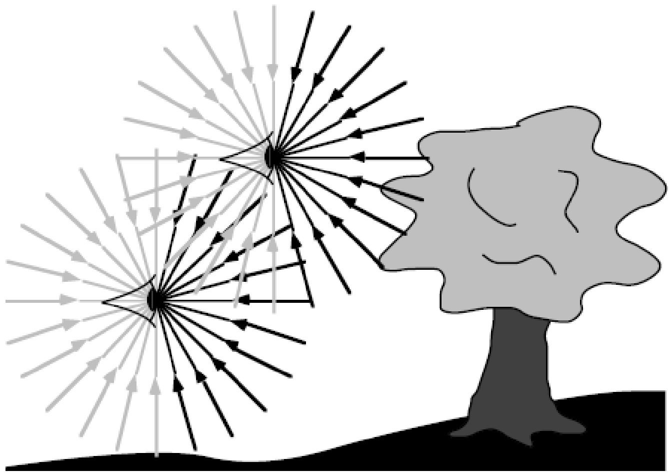




- For many applications, the additional information in 3D data quickly reaches diminishing returns and can even hurt performance since statistical models need to be more complex
- We have huge amounts of prior information and models for processing 2D data

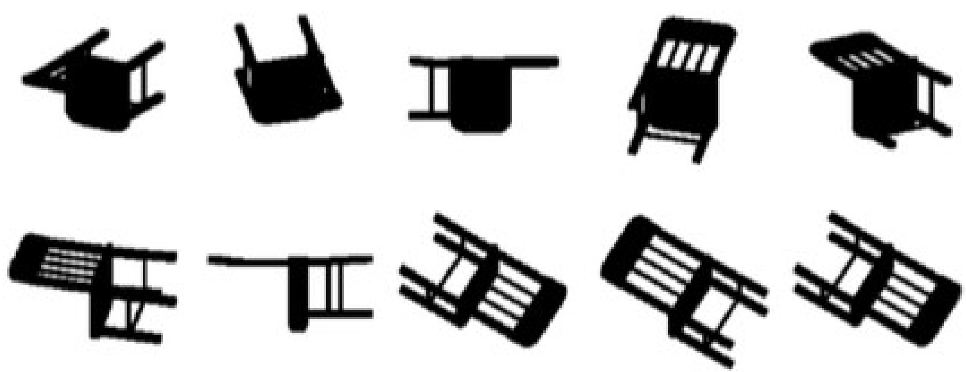
Light Field

- A **light field** (or **plenoptic function**) captures the radiance at a (3D) point along a (2D) direction
  - It is a 5D function
  - In free space, all points on a straight line have the same light field value in that direction, so reduces to a 4D function
  - With the free space assumption, a set of perspective images of an object from all possible directions constitutes its light field



Light Field Descriptor

- The **Light Field Descriptor** (LFD) of a 3D shape is a set of 2D images of it, taken from a 2D array of cameras
  - 20 cameras positioned at the vertices of a regular dodecahedron
  - Images rendered as silhouettes, so 10 unique views (say from a hemisphere)



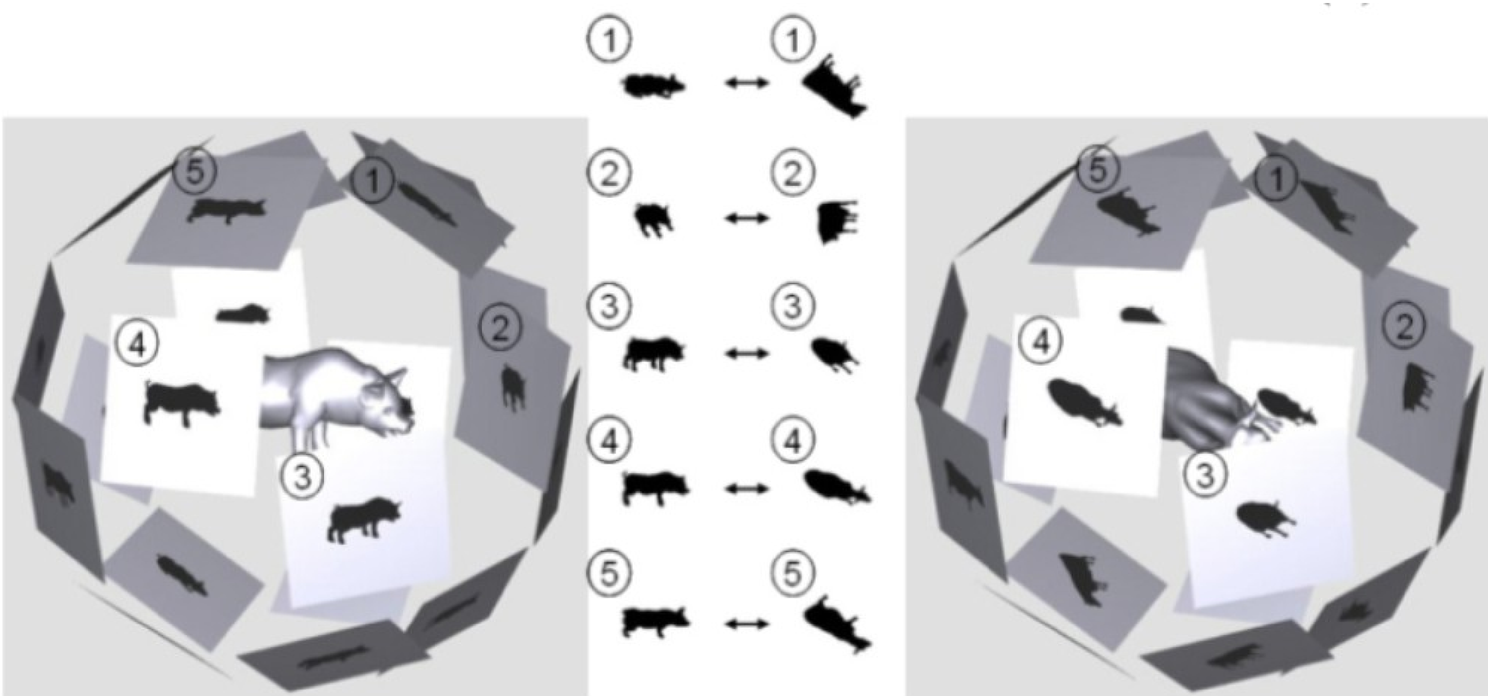
Comparing Shapes with LFD

- Consider two shapes

Chen et al., “On Visual Similarity Based 3D Model Retrieval”, 2003

Comparing Shapes with LFD

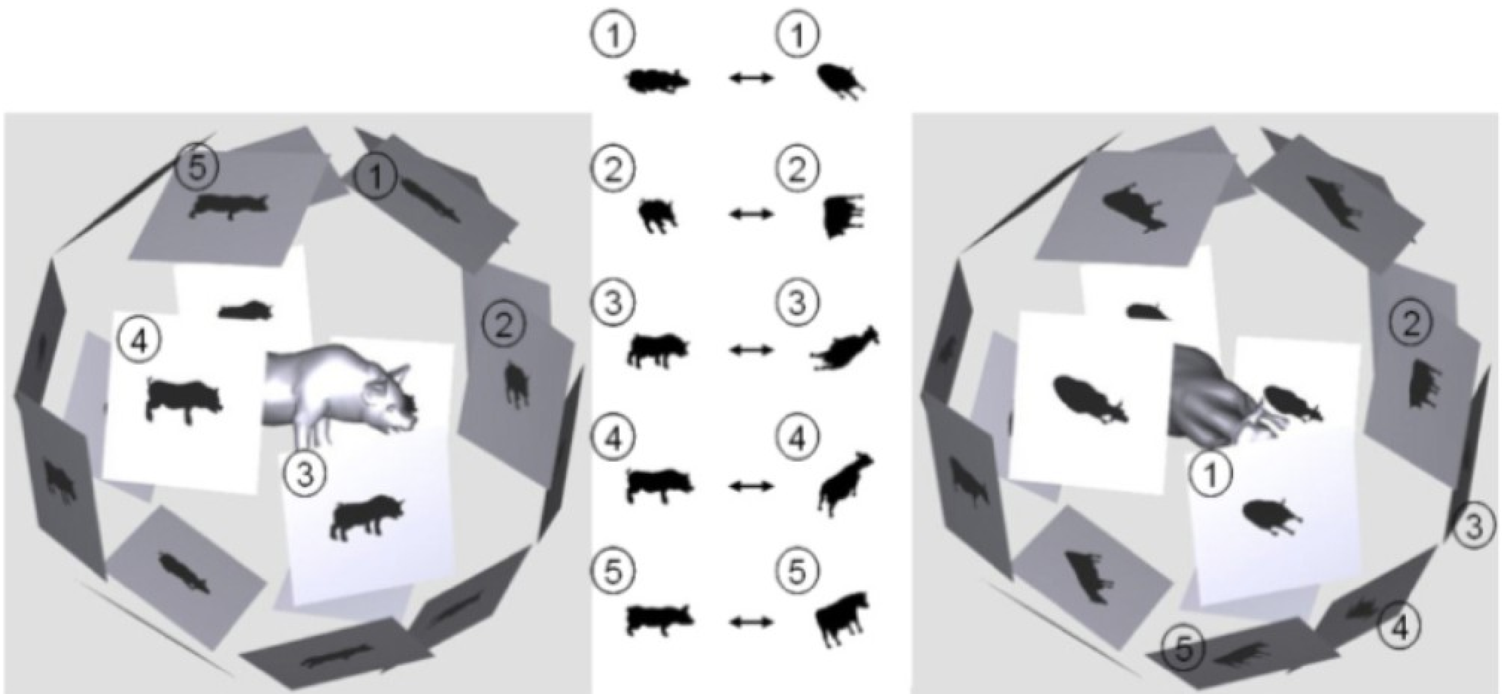
- A candidate rotation aligns the two sets of images
  - Comparing aligned image pairs gives a similarity metric



Chen et al., "On Visual Similarity Based 3D Model Retrieval", 2003

Comparing Shapes with LFD

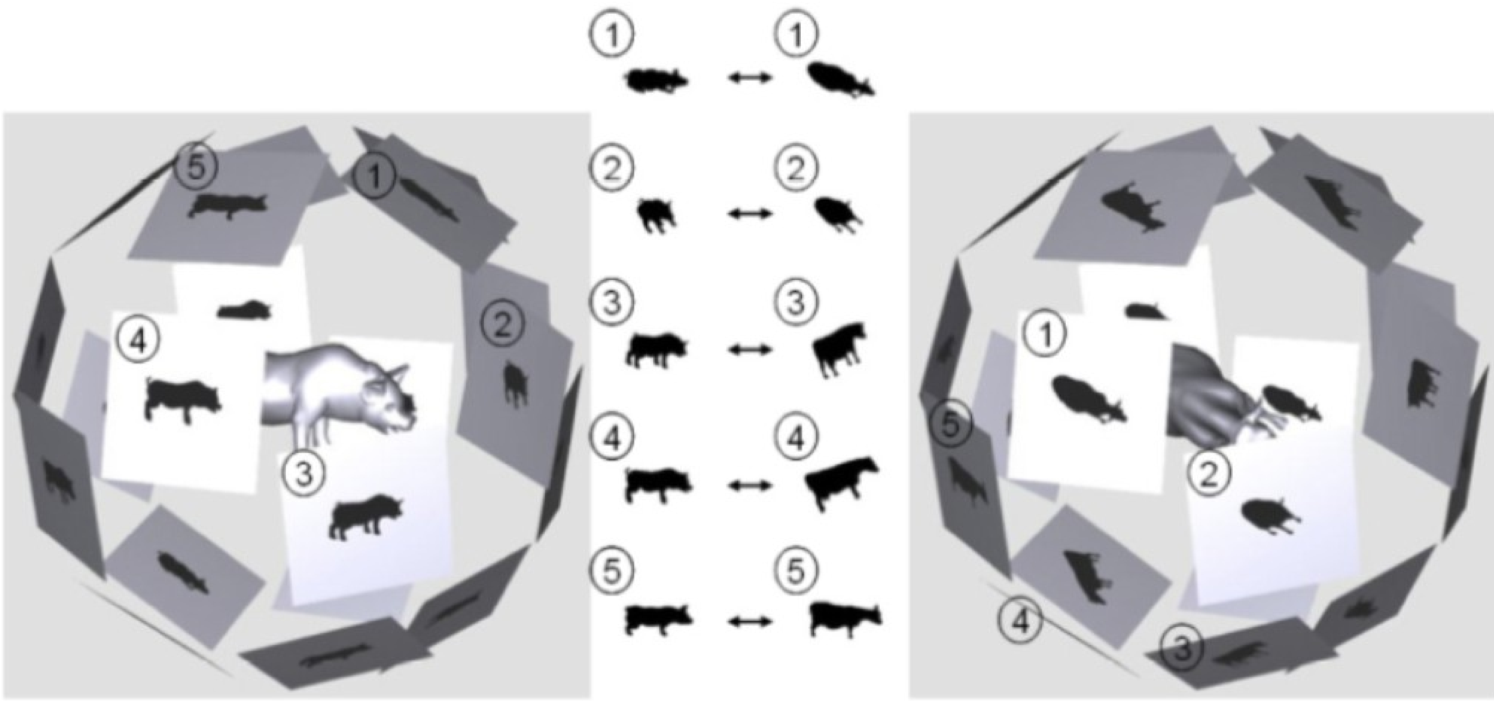
- Here's another candidate rotation
  - … which yields another similarity value



Chen et al., "On Visual Similarity Based 3D Model Retrieval", 2003

Comparing Shapes with LFD

- And another...



Chen et al., "On Visual Similarity Based 3D Model Retrieval", 2003

Comparing Shapes with LFD

- 60 different ways of aligning the dodecahedra
- The distance between two shapes A and B, with image sets $\{A_i\}$, $\{\mathrm{B}_i\}$ is

$$D(A, B) = \min_{r=1}^{60} \sum_{i=1}^{10} d_{\text{image}}(A_i, B_{rot(r,i)})$$

where $B_{rot(r,\, i)}$ is the image aligned to A_i by the r'th rotation

More views for more accuracy

- To increase chances of finding the right alignment, store image sets $\{A^j\}$ from N different dodecahedra ($N = 10$ in original paper)

$$D_{\mathrm{LFD}}(A, B) = \min_{j,k=1}^{N} D(A^j, B^k)$$

- $(N(N - 1) + 1) \times 60$ image comparisons (= 5460 in this case)

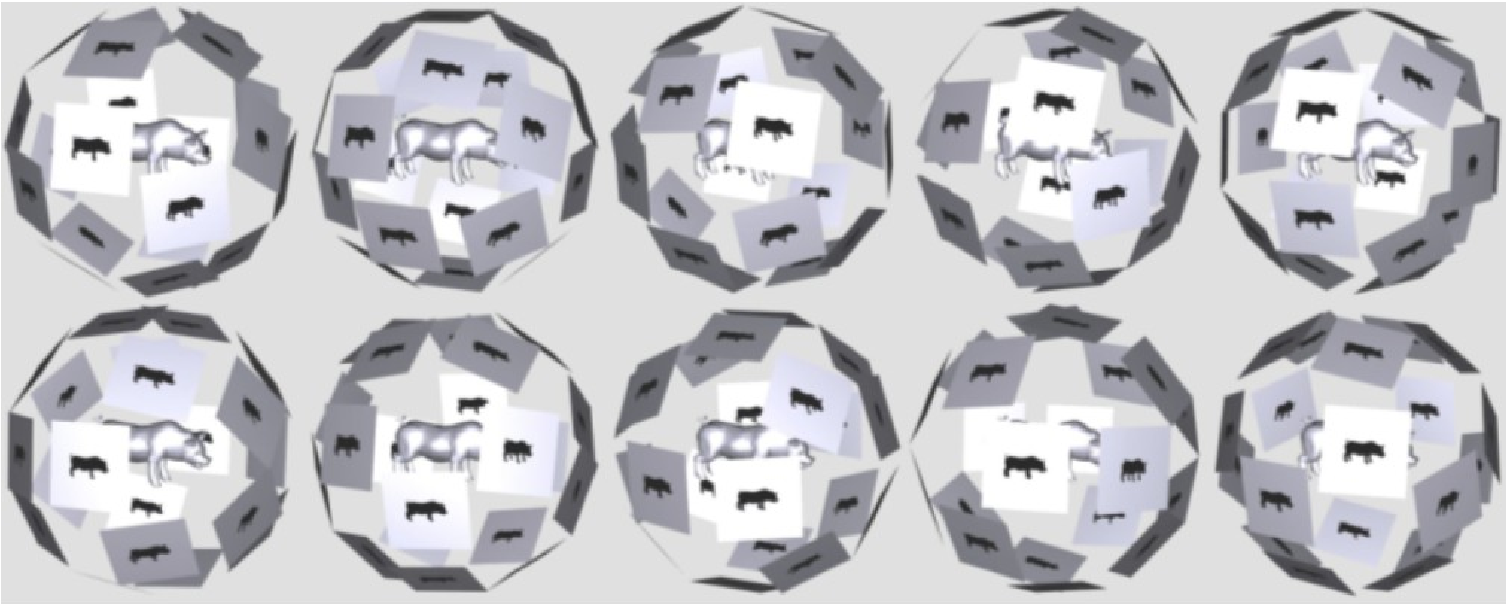


Image Comparison Metric

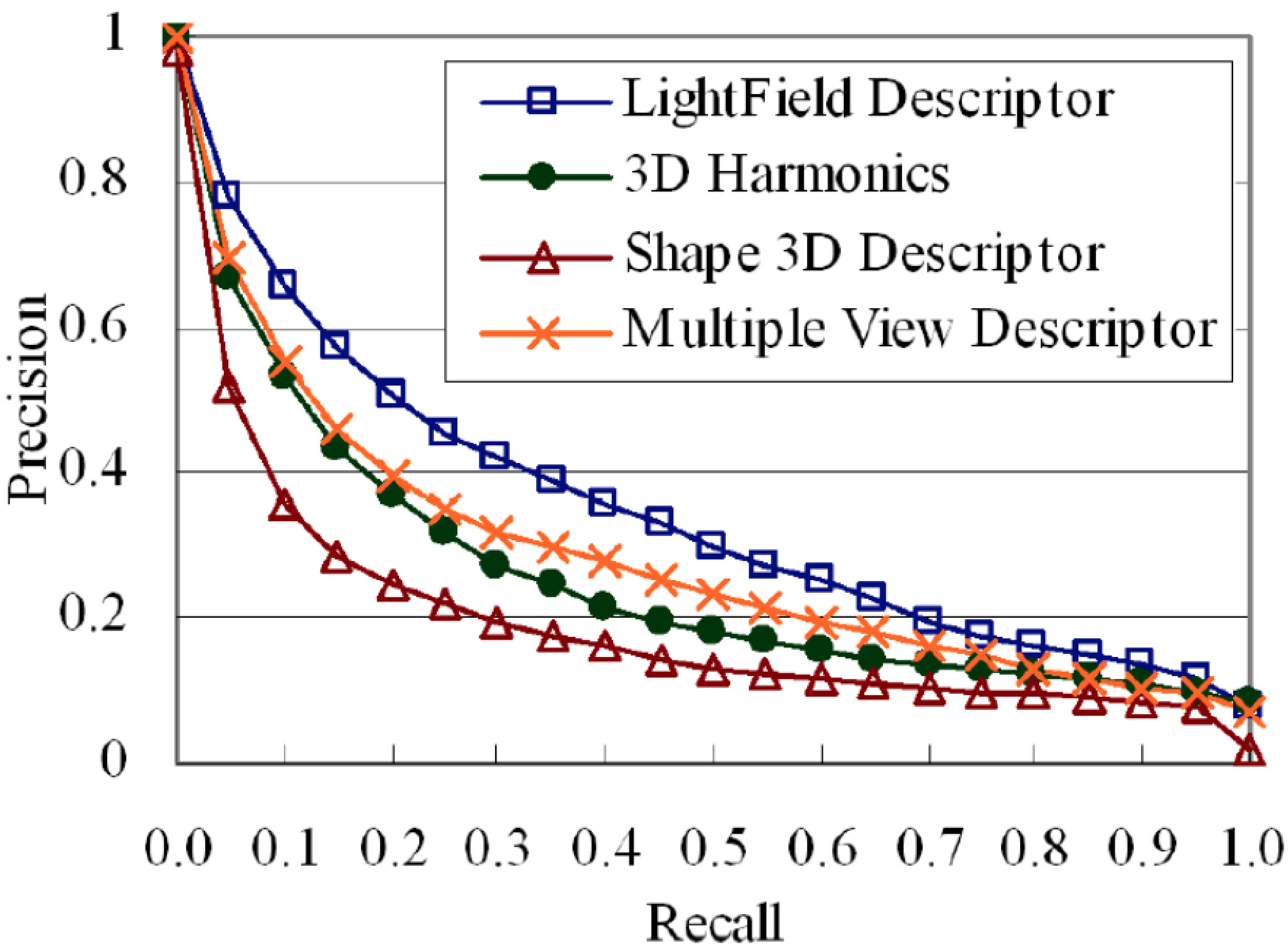
- Combine a "region-based" and a "contour-based" 2D descriptor
- Region-based descriptor
  - Combine information from all pixels in region
  - Do not emphasize boundary features
  - **Zernike Moment Descriptors** (ZMD) [35 8-bit coefficients]
- Contour-based descriptor
  - Captures only boundary information, ignoring interior
  - **Fourier Descriptors** (FD) [10 8-bit coefficients]

$$d_{\text{image}}(Img_1, Img_2) = \sum_{k=1}^{45} \left| C_{1,k} - C_{2,k} \right|$$

Querying Large Databases

- LFD is not a natural vector space (need to search over rotations), so can't apply traditional methods to accelerate nearest neighbor search
- Progressively refine descriptors for faster search
  - Use a few image sets, and a few highly quantized coefficients, to prune database and identify likely alignments
  - Progressively redo the search in the pruned database with more descriptors and more coefficients, using candidate alignments from the previous step

Results



3D Harmonics: discussed last class

Shape 3D Descriptor: curvature histograms

Multiple View Descriptor: align shapes using PCA, compare views along principal axes

Test database: 1833 shapes, with 549 shapes classified into 47 functional categories, the remaining shapes classified as "miscellaneous"

Properties of LFD

- Not very concise (100×45 coefficients)
- Reasonably quick to compute
- Not very efficient to match
- Good discrimination
- Invariant to rigid transformations
- Invariant to small deformations
- Insensitive to noise
- Insensitive to mesh topology
- Robust to degeneracies

What if we use better image descriptors?

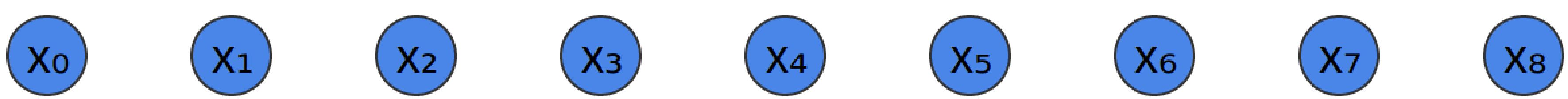
- ZMD/FD are ok, but hardly the state of the art in modern computer vision (circa 2016)
- Convolutional Neural Nets (CNNs) have revolutionized image recognition tasks

Model	Top-1	Top-5
Sparse coding [2]	47.1%	28.2%
SIFT + FVs [24]	45.7%	25.7%
CNN	**37.5%**	**17.0%**

In 2012, the error rate in the ImageNet visual recognition challenge was halved by a deep CNN (gains are typically incremental). There are 1000 categories: the baseline of random guessing would have a 99.9% error.

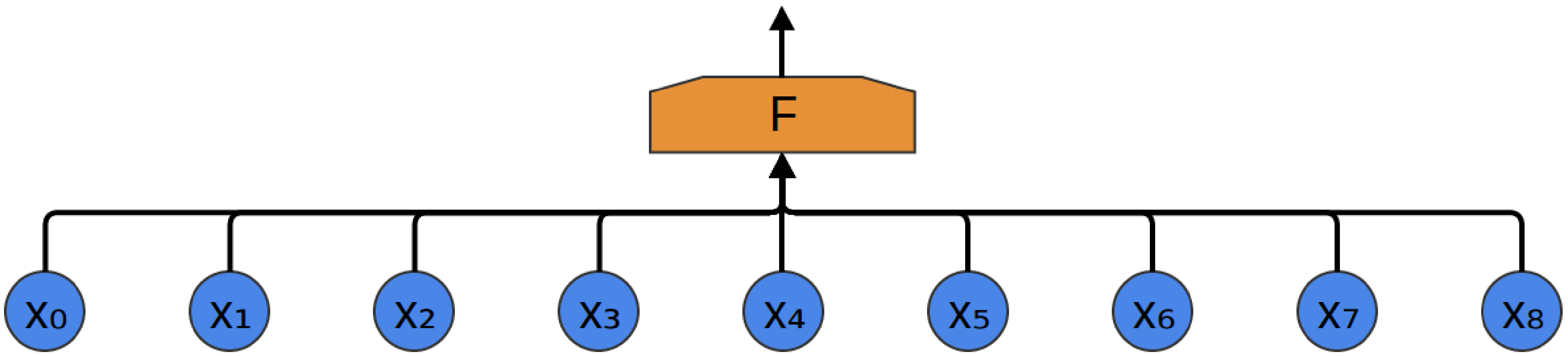
What is a Convolutional Neural Network?

- Imagine we have a set of N samples from some signal
- We want to produce a prediction, e.g. whether the signal represents a human voice, or a picture of a cat, or a depth image of a building



What is a Convolutional Neural Network?

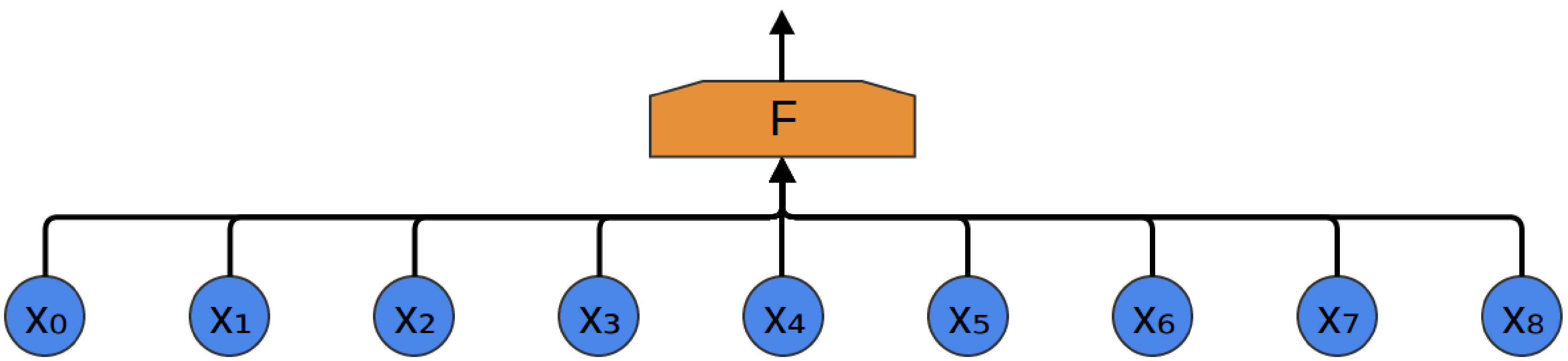
- We can compute the probability as a function F of these values
  - In a **fully-connected** network, the function takes in all the inputs at once, e.g. as $g(\mathbf{w}\cdot\mathbf{x})$, where $\mathbf{w}$ is a weight vector and g is some nonlinear transformation such as a sigmoid function



Christopher Olah

What is a Convolutional Neural Network?

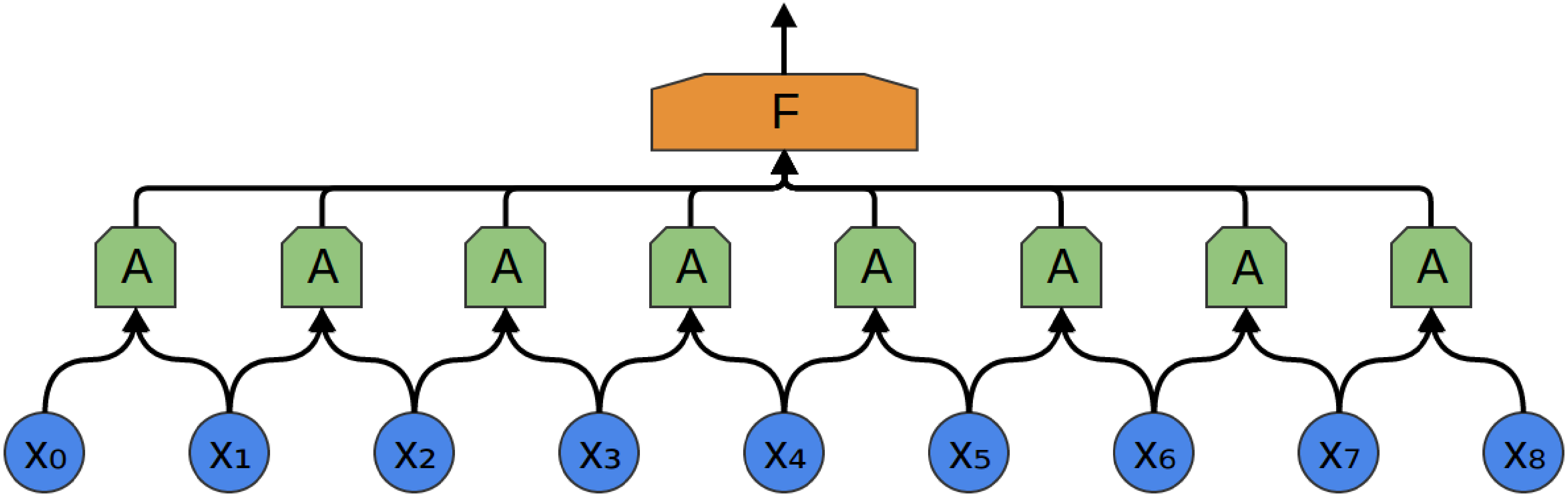
- Fully-connected networks have some drawbacks
  - The function is **very high-dimensional** (all inputs processed at once)
  - **No complex relationships** between inputs are modeled (just a dot product)
  - Local information is **not captured in a "translation-invariant" way** (a feature of the signal at the left end of the sequence must be learned independently of the same feature occurring at the right end)



Christopher Olah

What is a Convolutional Neural Network?

- **Solution:** a **convolutional layer**
- A filter (again, a dot product followed by a nonlinear transformation) is applied on local neighborhoods of the signal

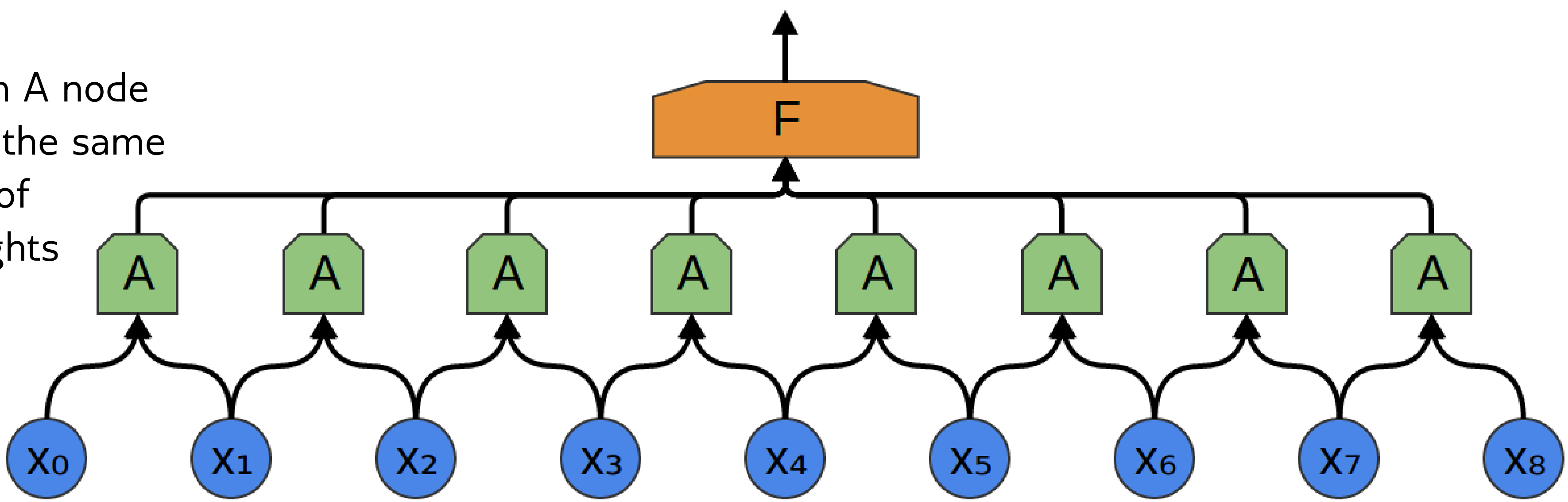


Christopher Olah

What is a Convolutional Neural Network?

- All filters **share the same weights**!
  - Dramatically reduces number of parameters of the network
- The final output is a function of the filter responses

Each A node has the same set of weights



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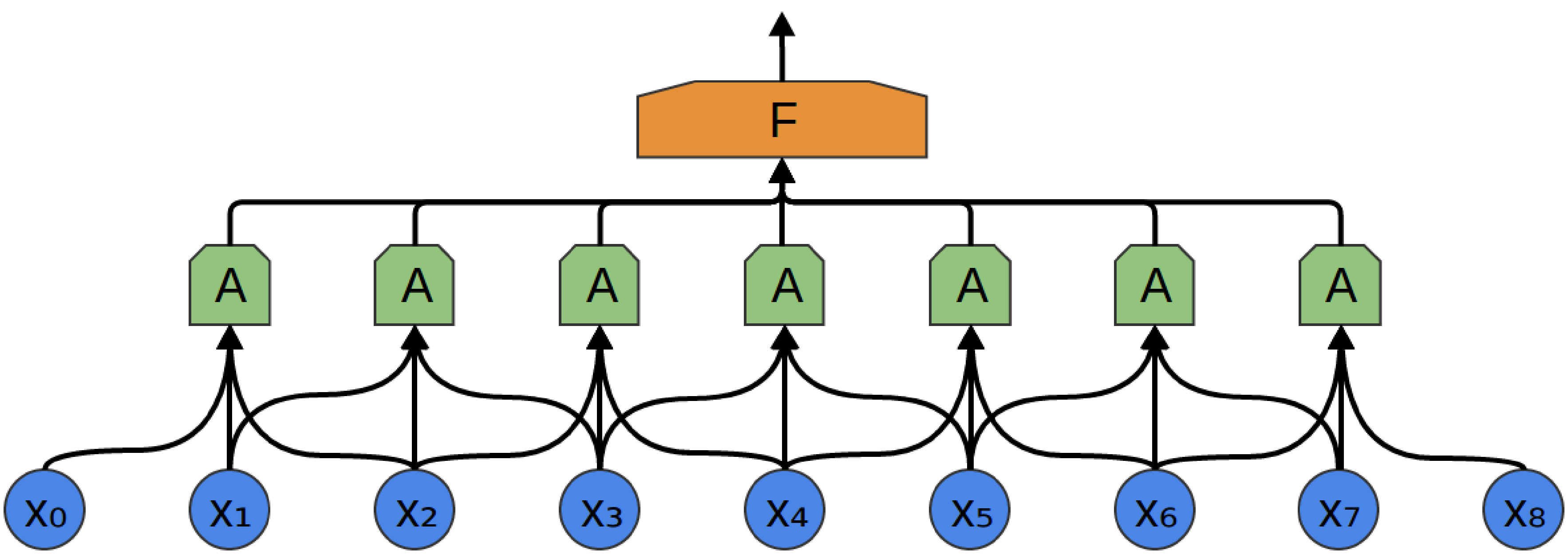
What is a Convolutional Neural Network?

- We can make the neighborhoods larger, to capture broader local features



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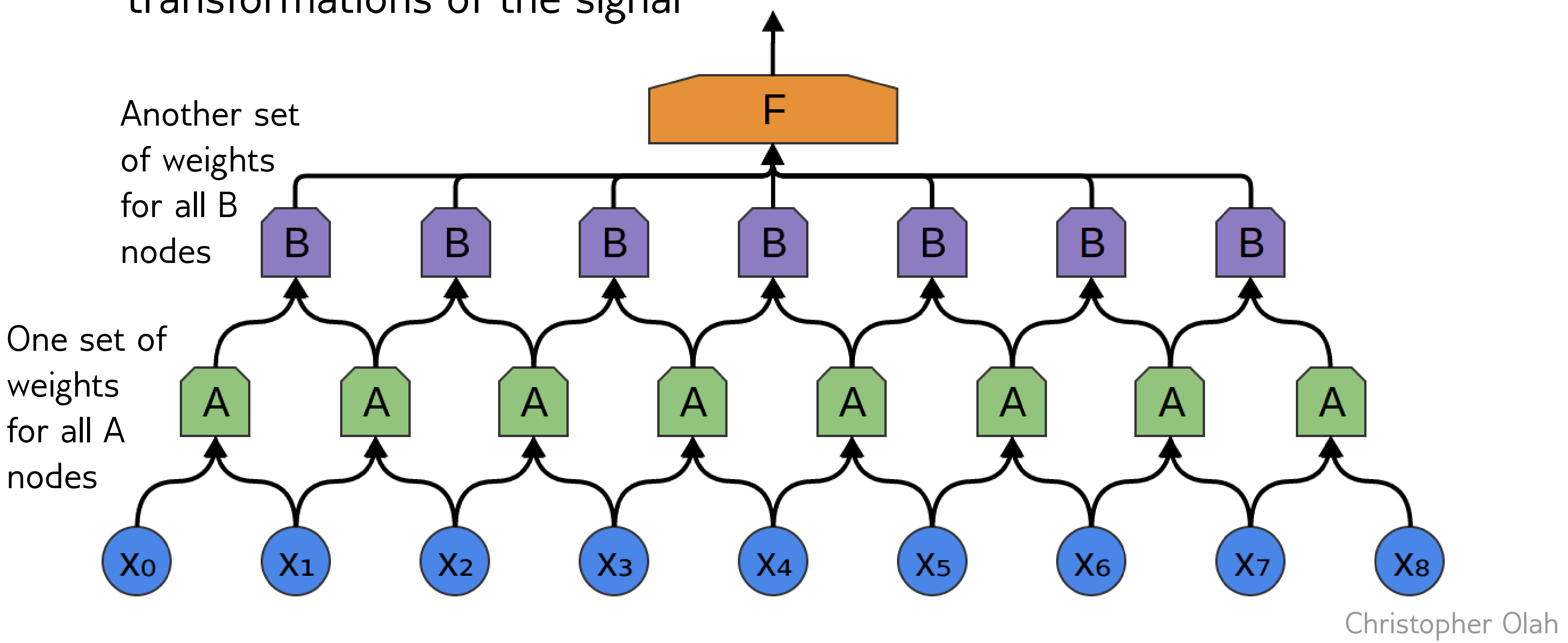
What is a Convolutional Neural Network?

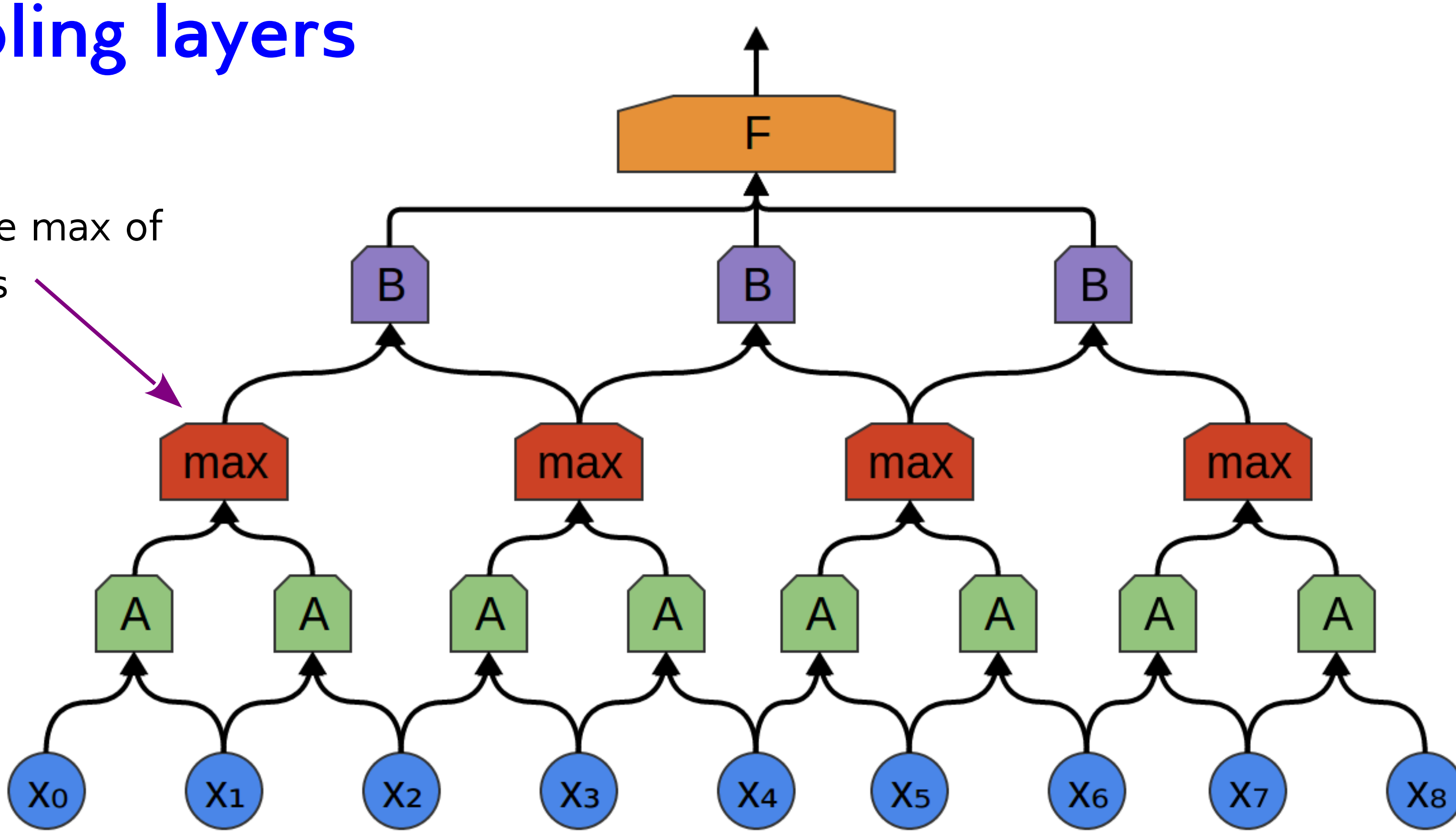
- Convolutional layers are **composable**: they can be stacked with each layer providing inputs for the next layer
  - Higher layers can capture more abstract features since they effectively cover larger neighborhoods, and combine multiple different nonlinear transformations of the signal



What is a Convolutional Neural Network?

- To make the network robust to small translations in detected features, and to reduce the amount of redundant data fed into higher layers, we introduce **pooling layers**

Return the max of the inputs



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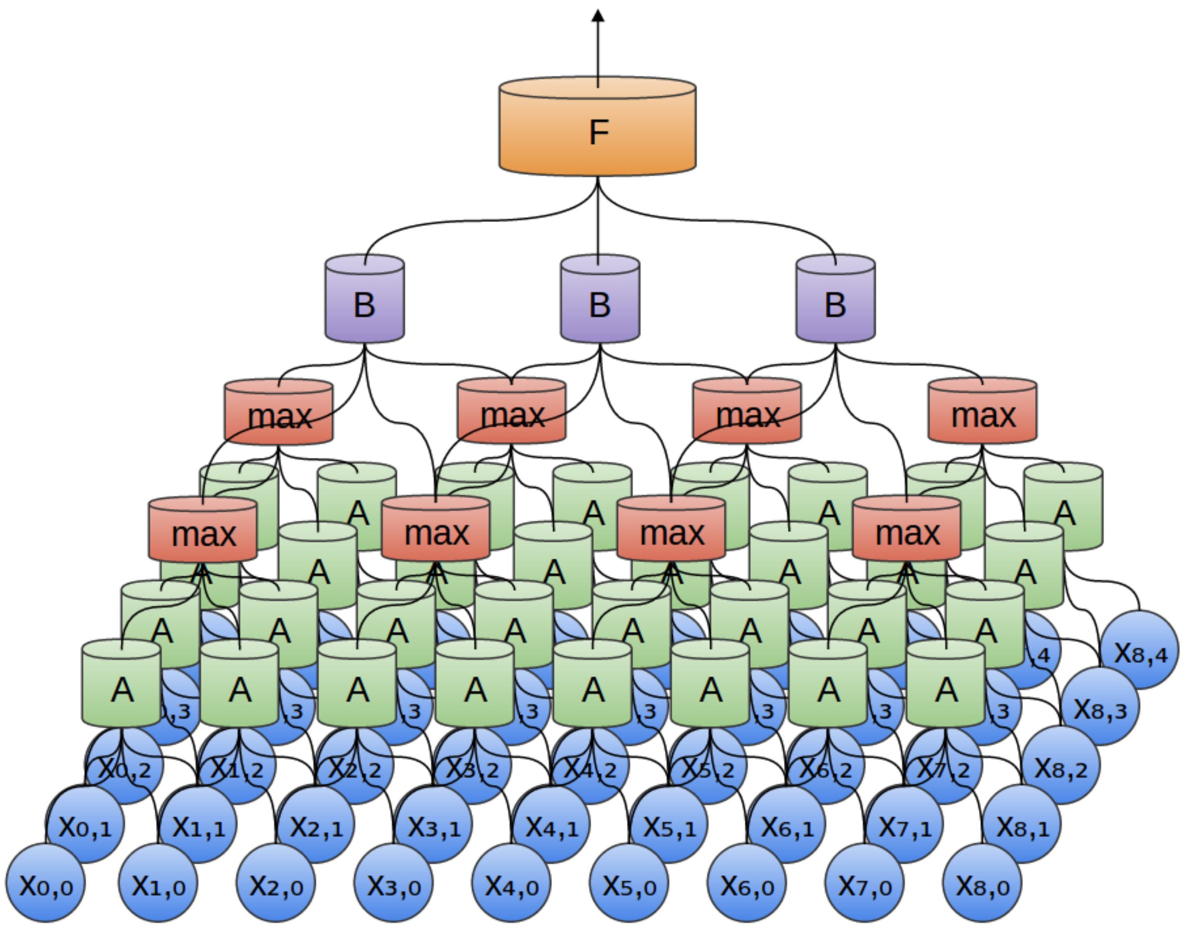
What is a Convolutional Neural Network?

- The signal can be 2D: the filters are now also 2D, but it's all essentially the same



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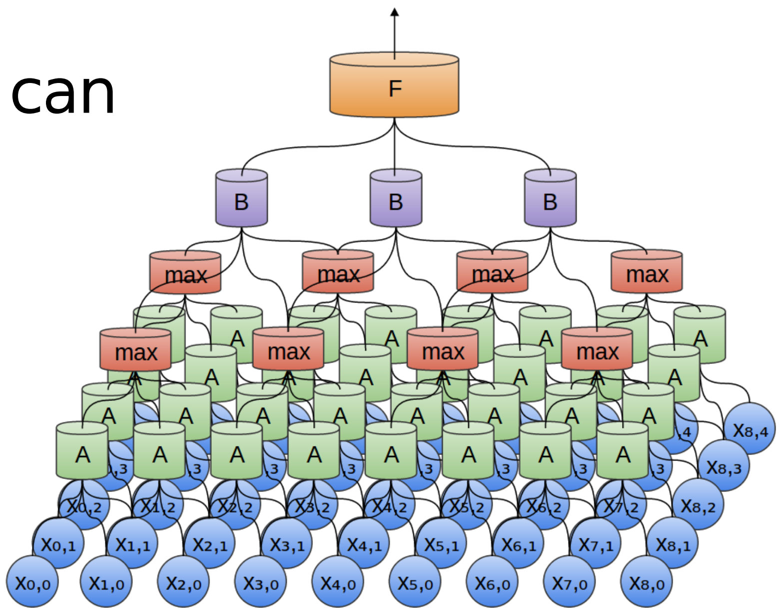
What is a Convolutional Neural Network?

- The function computed by this gigantic model is **differentiable*** w.r.t. the weights
  - Given training data and a **loss function** measuring the deviation between predicted and actual values, we can optimize the weights by gradient descent
  - The gradient of the loss function can be found efficiently by a method called **back-propagation**

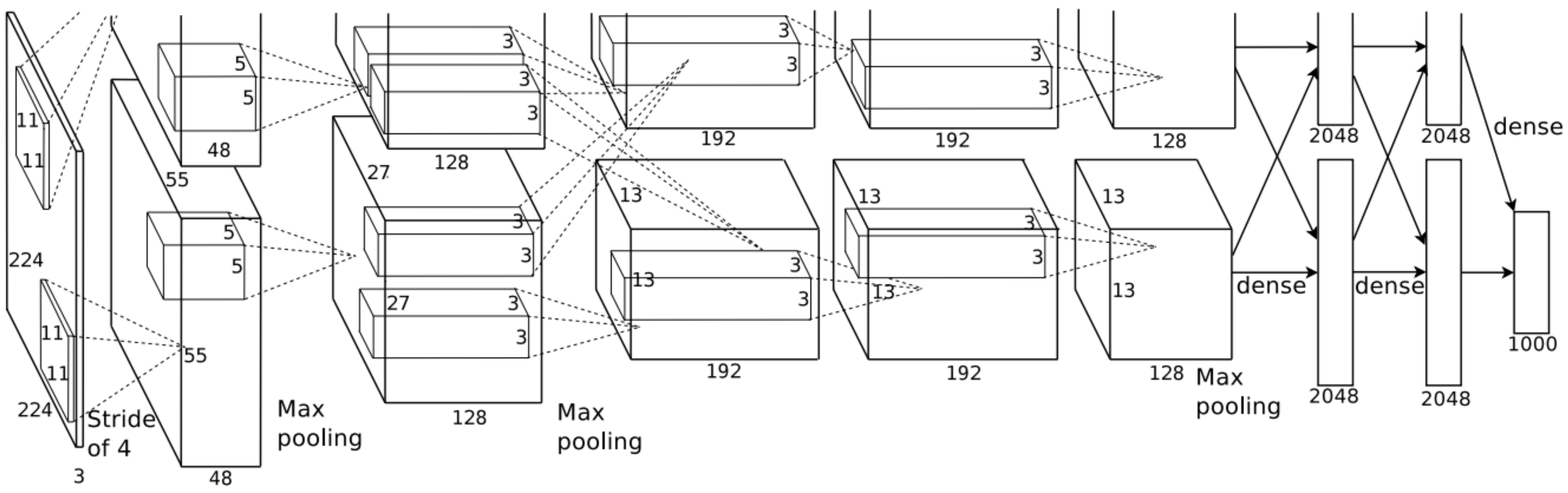


* nearly everywhere

Christopher Olah

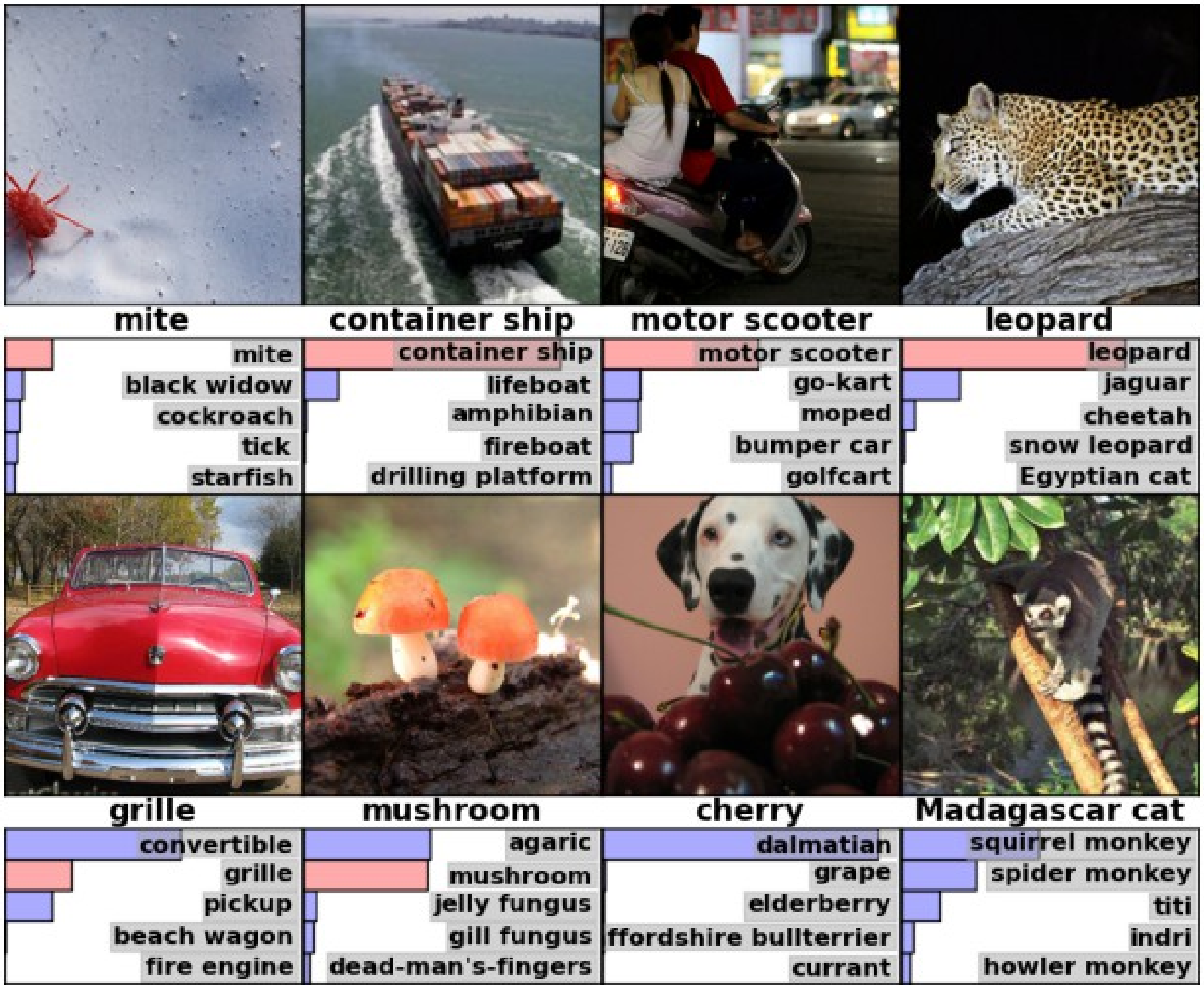
A real-world CNN

- 5 convolutional layers, 3 max-pooling layers, 3 fully-connected layers
- ~60 million parameters (despite the weight sharing!)



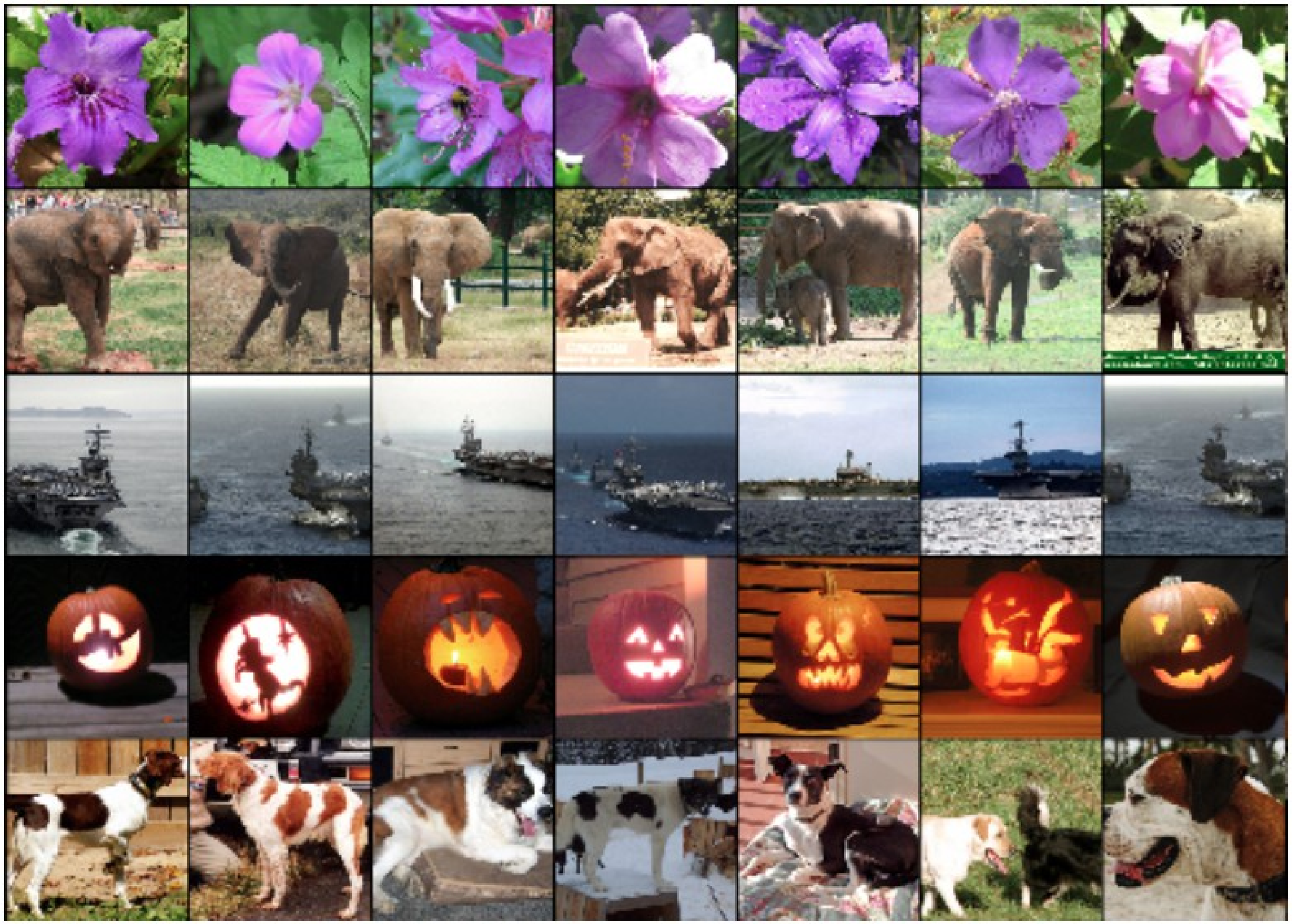
Krizhevsky, Sutskever and Hinton, 2012

Using the CNN for **classification**



Krizhevsky, Sutskever and Hinton, 2012

Using the CNN for **retrieval**



Query   Top 6 results

The descriptor is the vector of neuron activations in the second last layer

Krizhevsky, Sutskever and Hinton, 2012

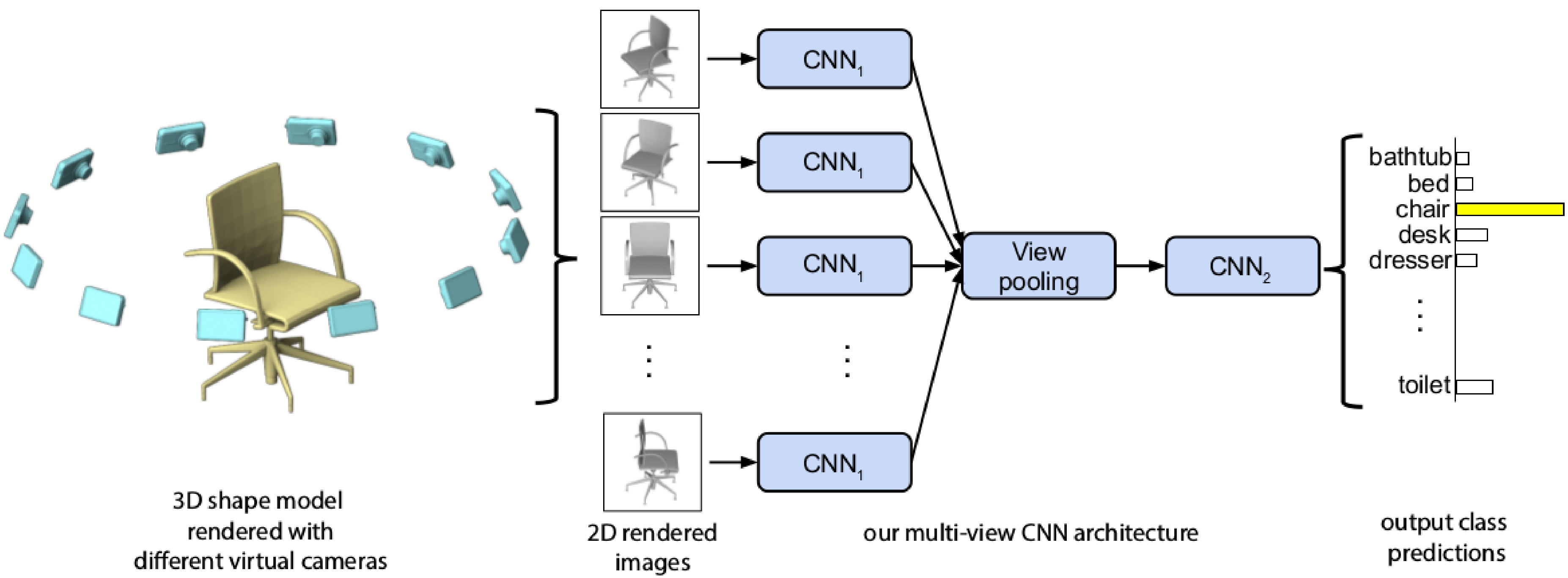
Image CNN for 3D shapes

- Let's take a CNN trained on a (huge) image database, and use it to analyze views of 3D shapes
  - **Render** a 3D shape from an arbitrary viewpoint
  - Pass it through the **pre-trained CNN** and take the neuron activations in the second-last layer as the descriptor
  - For more accuracy, **fine-tune** the network on a training set of rendered shapes before testing
- Just this alone, with a single view (from an unknown direction) of the shape, bumps up the mAP retrieval accuracy (area under PR curve) on a 40-class, 12K-shape collection from 40.9% (LFD) to **61.7%.**
  - An LFD-like approach with 12 views/shape further improves to **62.8%**

Su et al., "Multi-view Convolutional Neural Networks for 3D Shape Recognition", 2015

Combining Views

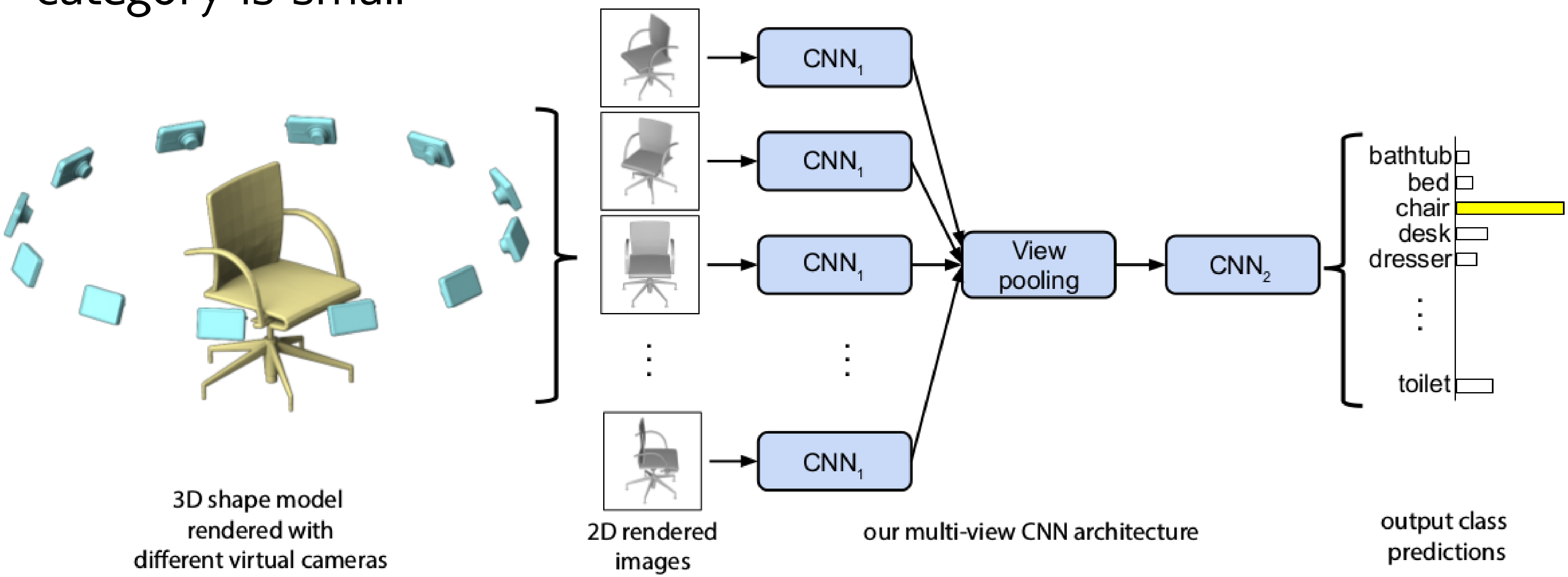
- A smarter way to aggregate information from multiple views
  - Take the output signal of the last convolutional layer of the base network (CNN_1) from each view, and combine them, element-by-element, using a max-pooling operation
  - Pass this **view-pooled** signal through the rest of the network (CNN_2)



Su et al., "Multi-view Convolutional Neural Networks for 3D Shape Recognition", 2015

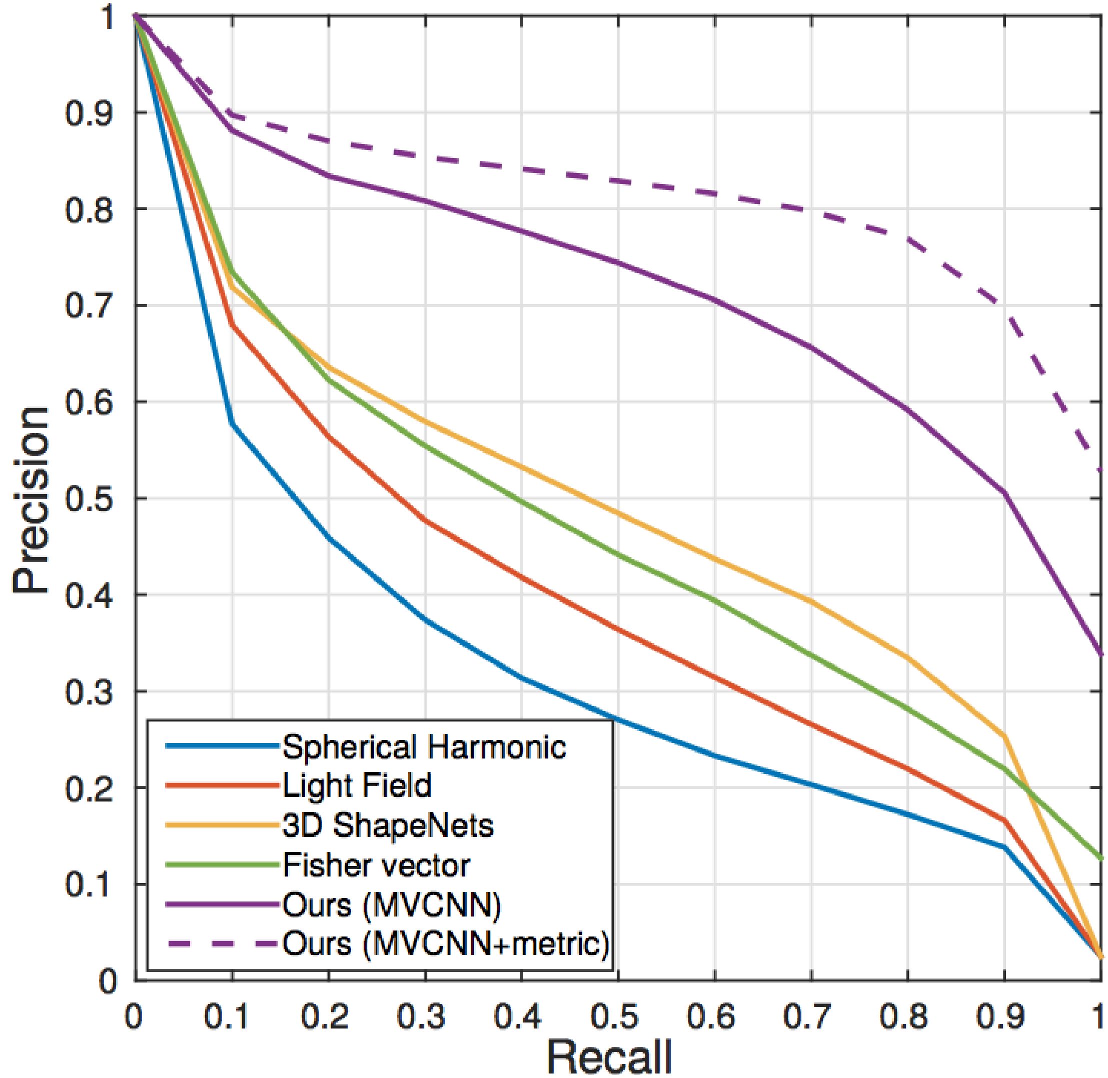
Combining Views

- The view-pooled CNN can still be trained (in exactly the same way) using back-propagation and gradient descent
- For retrieval, the descriptor from the second-last layer can be further tuned by learning a Mahalanobis metric (a projection of the descriptors) where the distance between shapes of the same training category is small



Su et al., "Multi-view Convolutional Neural Networks for 3D Shape Recognition", 2015

How well does this work?



Su et al., "Multi-view Convolutional Neural Networks for 3D Shape Recognition", 2015

How well does this work?

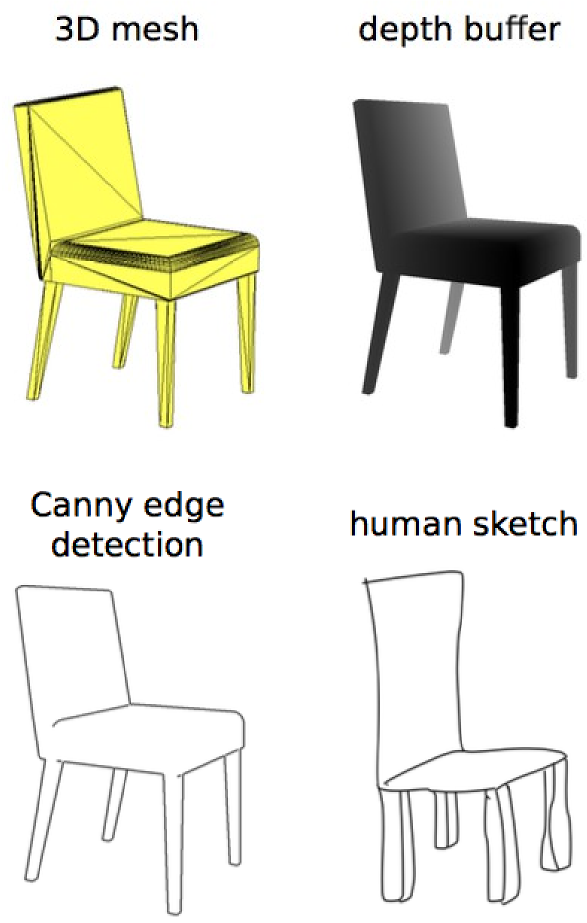
Method	Training Config.			Test Config.	Classification (Accuracy)	Retrieval (mAP)
	Pre-train	Fine-tune	#Views	#Views		
(1) SPH [16]	-	-	-	-	68.2%	33.3%
(2) LFD [5]	-	-	-	-	75.5%	40.9%
(3) 3D ShapeNets [37]	ModelNet40	ModelNet40	-	-	77.3%	49.2%
(4) FV	-	ModelNet40	12	1	78.8%	37.5%
(5) FV, 12×	-	ModelNet40	12	12	84.8%	43.9%
(6) CNN	ImageNet1K	-	-	1	83.0%	44.1%
(7) CNN, f.t.	ImageNet1K	ModelNet40	12	1	85.1%	61.7%
(8) CNN, 12×	ImageNet1K	-	-	12	87.5%	49.6%
(9) CNN, f.t.,12×	ImageNet1K	ModelNet40	12	12	88.6%	62.8%
(10) MVCNN, 12×	ImageNet1K	-	-	12	88.1%	49.4%
(11) MVCNN, f.t., 12×	ImageNet1K	ModelNet40	12	12	89.9%	70.1%
(12) MVCNN, f.t.+metric, 12×	ImageNet1K	ModelNet40	12	12	89.5%	**80.2%**
(13) MVCNN, 80×	ImageNet1K	-	80	80	84.3%	36.8%
(14) MVCNN, f.t., 80×	ImageNet1K	ModelNet40	80	80	**90.1%**	70.4%
(15) MVCNN, f.t.+metric, 80×	ImageNet1K	ModelNet40	80	80	**90.1%**	79.5%

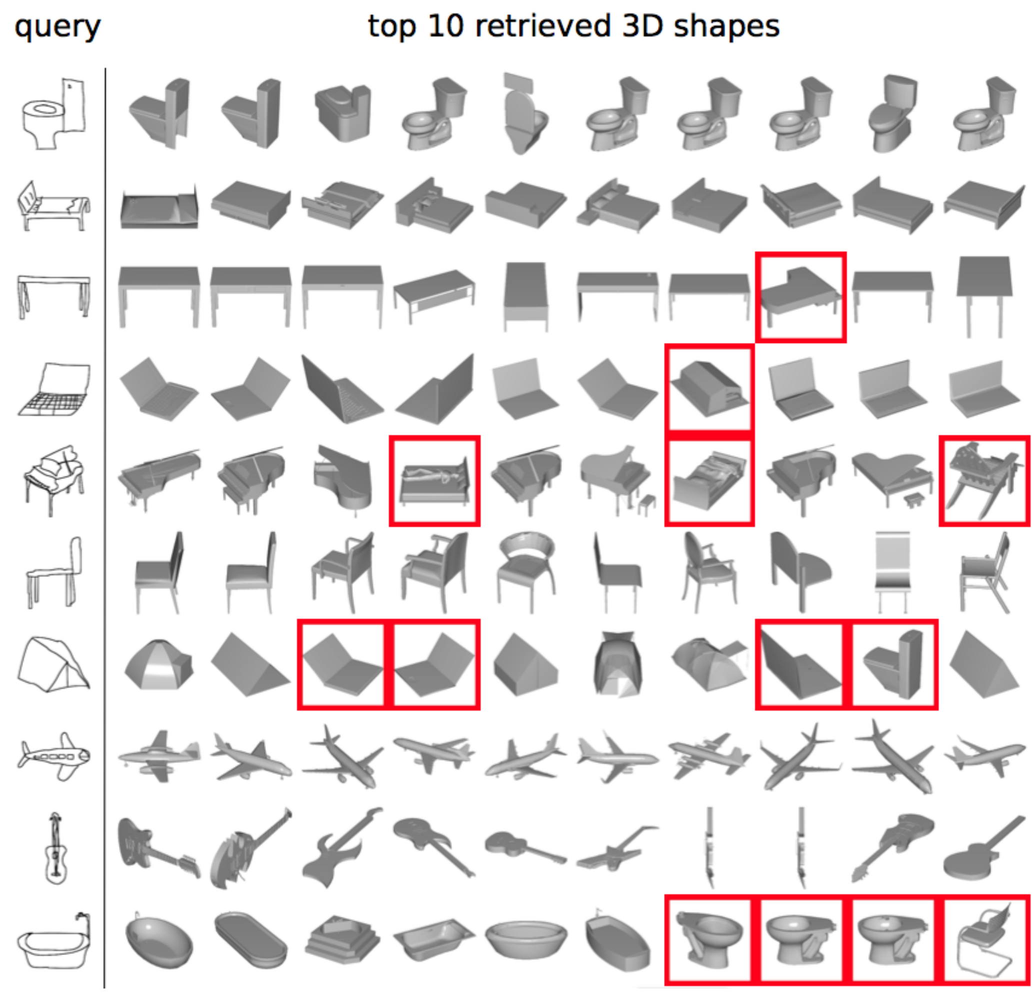
* f.t.=fine-tuning, metric=low-rank Mahalanobis metric learning

Su et al., “Multi-view Convolutional Neural Networks for 3D Shape Recognition”, 2015

A side benefit of view-based representations

- The MVCNN can be fine-tuned to retrieve 3D models based on hand-drawn 2D sketches





Properties of MVCNN

- Not very concise (4096 second-last layer neurons)
- Reasonably quick to compute (render and pass through CNN)
- Efficient to compare (natural vector space)
- Good discrimination
- Invariant to rigid transformations
- Invariant to small deformations
- Insensitive to noise
- Insensitive to mesh topology
- Robust to degeneracies