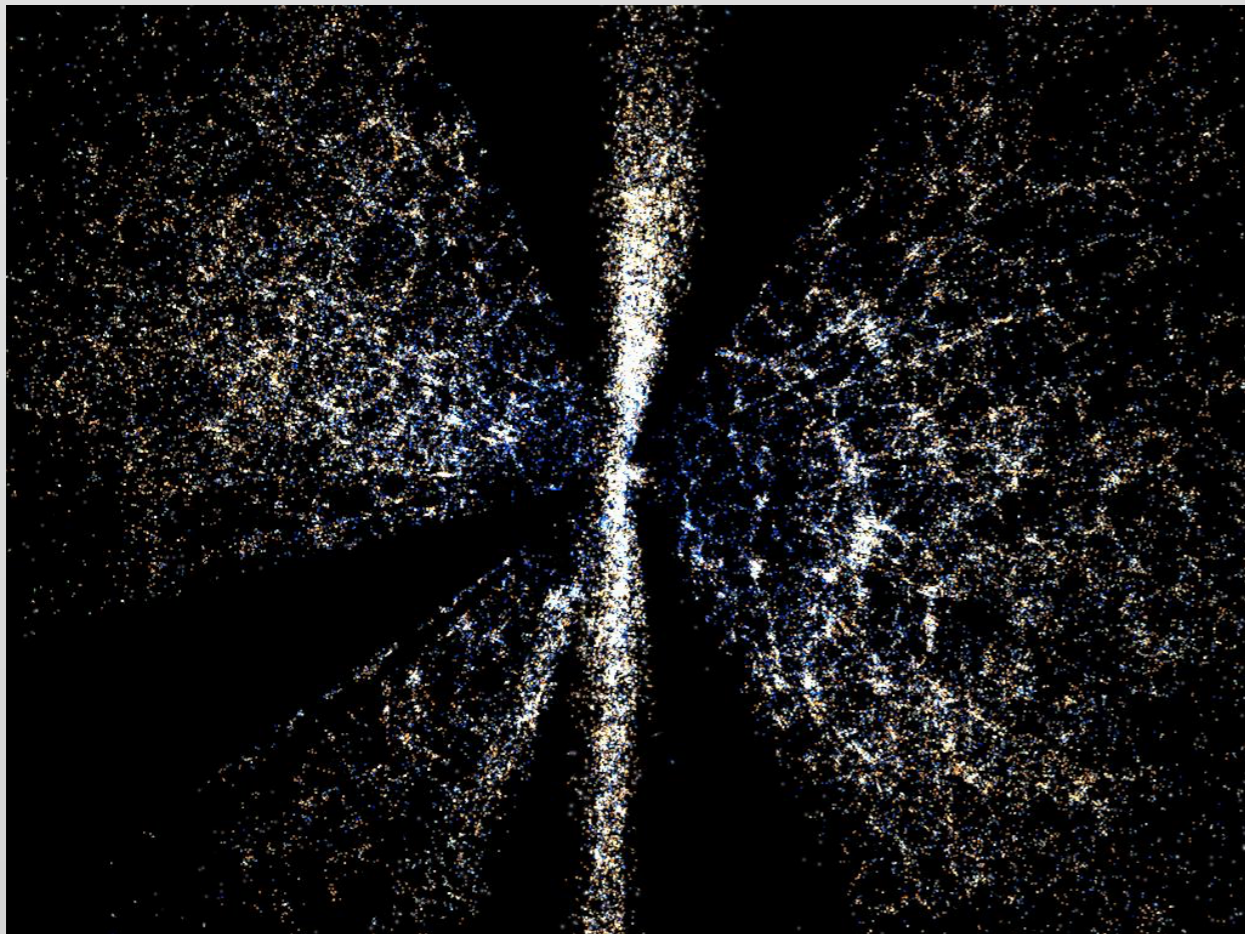


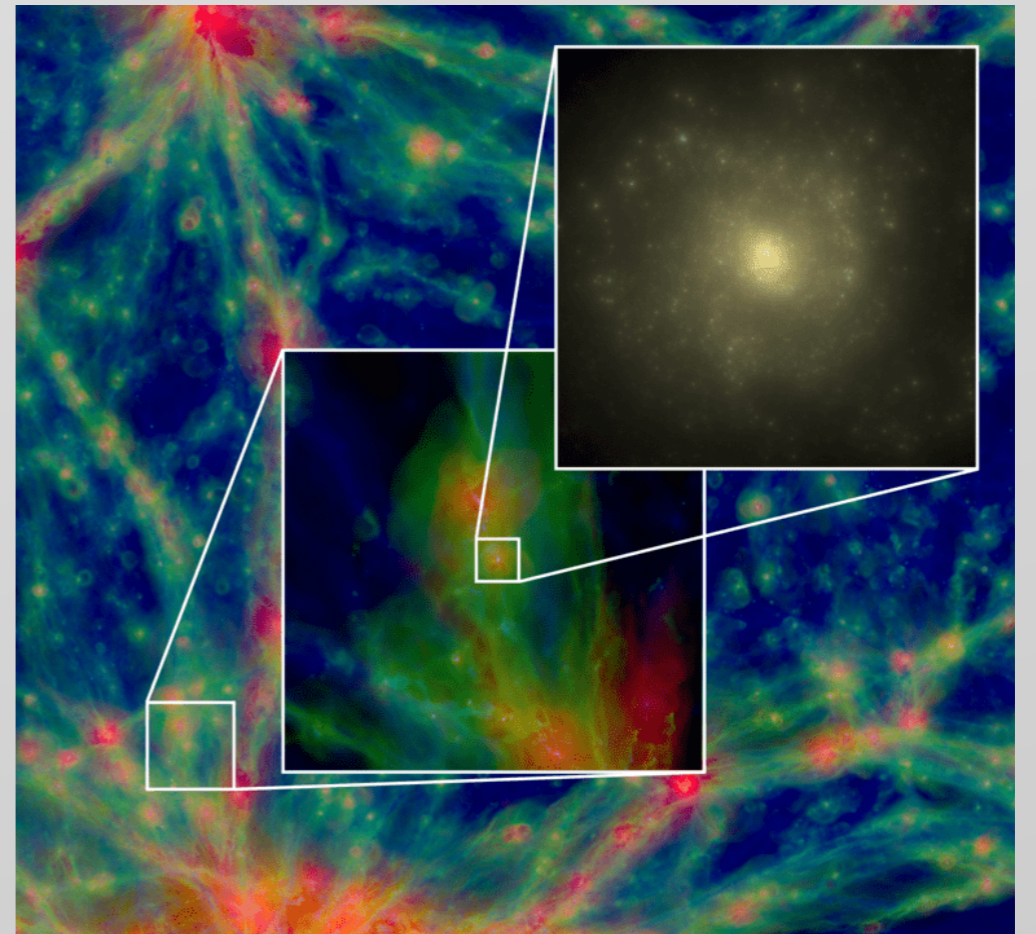
|

AI in the data era

# Astronomy in the data era



SDSS



Eagle simulation



## Radio frequency interference mitigation using deep convolutional neural networks

Joël Akeret<sup>a,\*</sup>, Chihway Chang<sup>a</sup>, Aurelien Lucchi<sup>b</sup>, Alexandre Refregier<sup>a</sup>

## Measuring photometric redshifts using galaxy images and Deep Neural Networks

Ben Hoyle

## Automated Distant Galaxy Merger Classifications from Space Telescope Images using the Illustris Simulation

Gregory F. Snyder<sup>1</sup>, Vicente Rodriguez-Gomez<sup>2</sup>, Jennifer M. Lotz<sup>1</sup>, Paul Torrey<sup>3,4</sup>, Amanda C.N. Quirk<sup>1,5</sup>, Lars Hernquist<sup>6</sup>, Mark Vogelsberger<sup>3</sup>, Peter E. Freeman<sup>7</sup>

<sup>1</sup> Space Telescope Science Institute, 3700 San Martin Dr, Baltimore, MD 21218

<sup>2</sup> Department of Physics & Astronomy, Johns Hopkins University, 3400 N Charles St, Baltimore, MD 21218, USA

<sup>3</sup> Department of Physics, Kavli Institute for Astrophysics & Space Research, Massachusetts Institute of Technology, Cambridge, MA, 02139, USA

<sup>4</sup> Department of Astronomy, University of Florida, 211 Bryant Space Science Center, Gainesville, FL, 32611, USA

<sup>5</sup> Department of Astronomy & Astrophysics, UC Santa Cruz, 1156 High St, Santa Cruz, CA 95064

<sup>6</sup> Harvard-Smithsonian Center for Astrophysics, 60 Garden St, Cambridge, MA, 02138, USA

<sup>7</sup> Department of Statistics, Carnegie Mellon University, 5000 Forbes Avenue, Pittsburgh, PA 15213, USA

## Quasar microlensing light curve analysis using deep machine learning

Georgios Vernardos,<sup>1\*</sup> and Grigorios Tsagkatakis<sup>2</sup>

<sup>1</sup>Kapteyn Astronomical Institute, University of Groningen, PO Box 800, NL-9700AV Groningen, the Netherlands

<sup>2</sup>Institute of Computer Science - Foundation for Research and Technology (FORTH), GR-71110, Heraklion, Greece

## CLASSIFYING RADIO GALAXIES WITH CONVOLUTIONAL NEURAL NETWORK

A. K. ANIYAN

Department of Physics and Electronics, Rhodes University, Grahamstown, South Africa  
and

SKA South Africa, 3<sup>rd</sup> Floor, The Park, Cape Town, South Africa

K. THORAT

Department of Physics and Electronics, Rhodes University  
and

SKA South Africa, 3<sup>rd</sup> Floor, The Park, Cape Town, South Africa

## Forging new worlds: high-resolution synthetic galaxies with chained generative adversarial networks

Levi Fussell,<sup>1\*</sup> Ben Moews,<sup>2</sup>

<sup>1</sup>Institute of Perception, Action and Behaviour, University of Edinburgh, 10 Crichton St, Edinburgh EH8 9AB, UK

<sup>2</sup>Institute for Astronomy, University of Edinburgh, Royal Observatory, Edinburgh EH9 3HJ, UK

# Radio frequency interference mitigation using deep convolutional neural networks

Joël Akeret<sup>a,\*</sup>, Chihway Chang<sup>a</sup>, Aurelien Lucchi<sup>b</sup>, Alexandre Refregier<sup>a</sup>

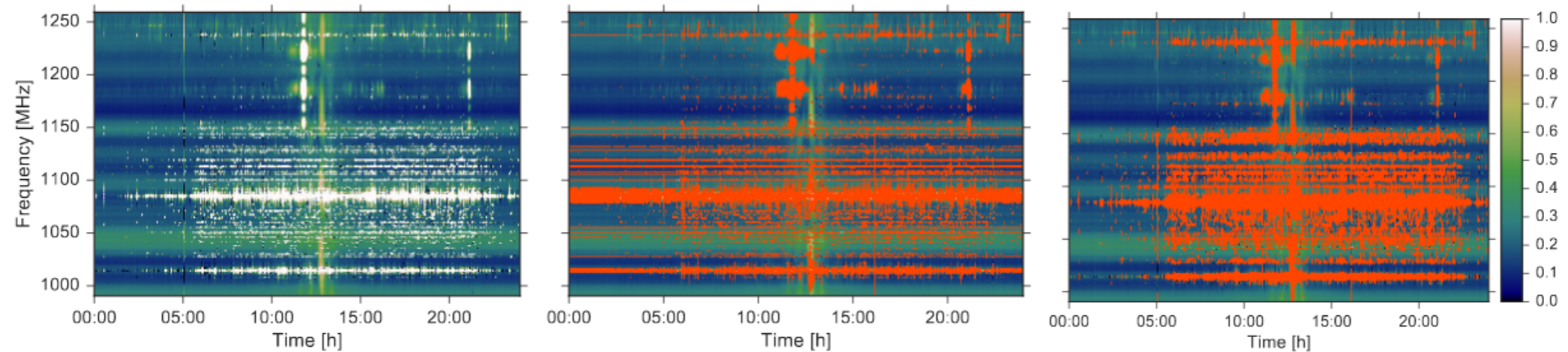
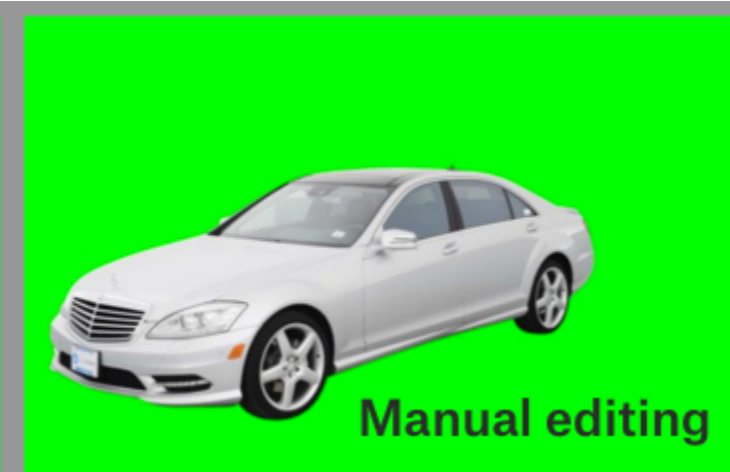
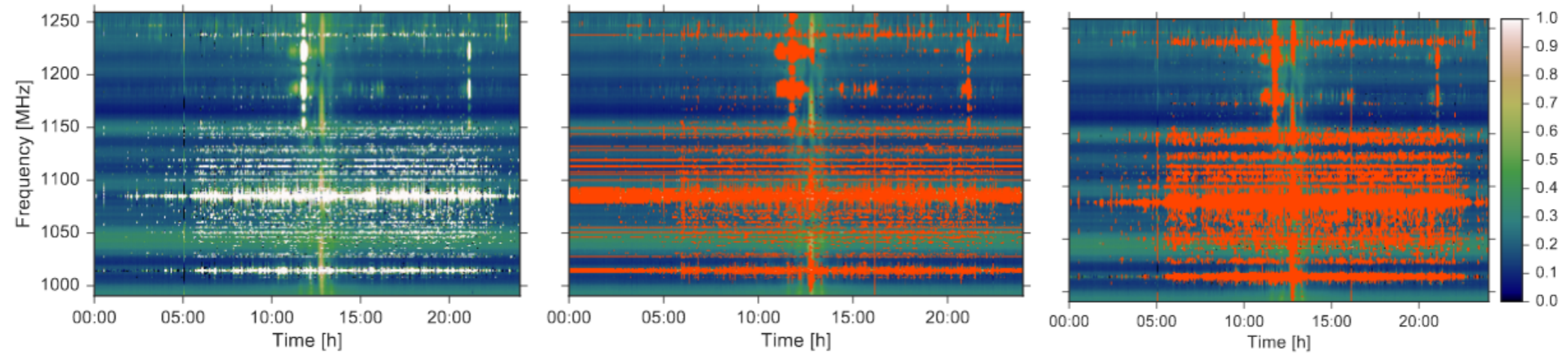


Figure 2: The left panel displays 24 hours of observed TOD from the Bleien Observatory. The broadband RFI contamination mainly comes from the nearby airport and is visible in the 1025–1150 MHz frequency band. The TOD also demonstrates the variation in the RFI level between day and night as the amount of RFI clearly increased at around 6:00 am and decreased at 11:00 pm. The central panel shows the same TOD overlaid (orange) with the RFI mask obtained from SEEK's SUMTHRESHOLD. The right panel displays the RFI mask from our U-Net with 3 layers and 64 features.

# Radio frequency interference mitigation using deep convolutional neural networks

Joël Akeret<sup>a,\*</sup>, Chihway Chang<sup>a</sup>, Aurelien Lucchi<sup>b</sup>, Alexandre Refregier<sup>a</sup>



# Star masking

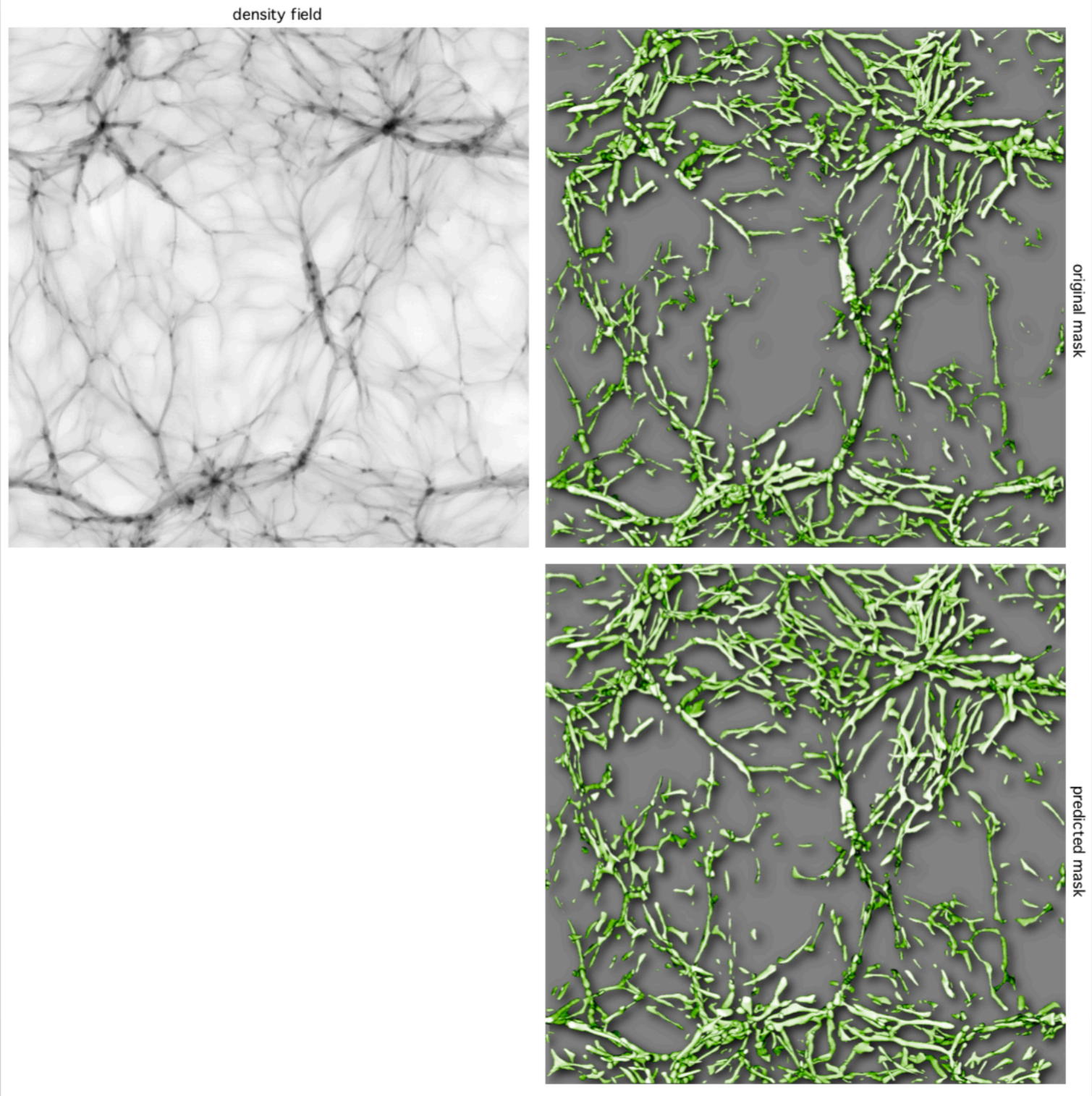


Original

Mask

Predicted

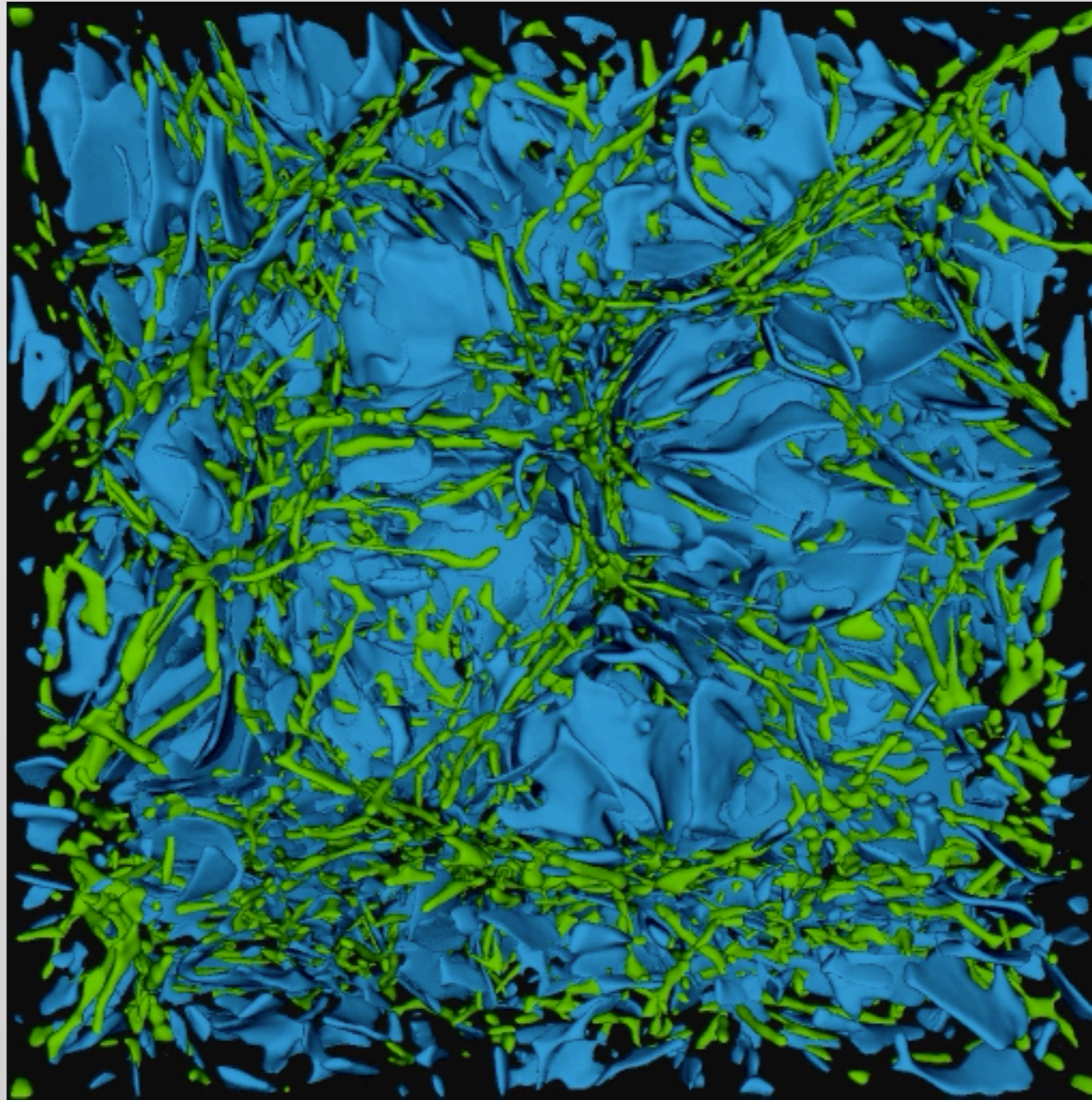
# Automatic cosmic web segmentation



Aragon-Calvo 2019

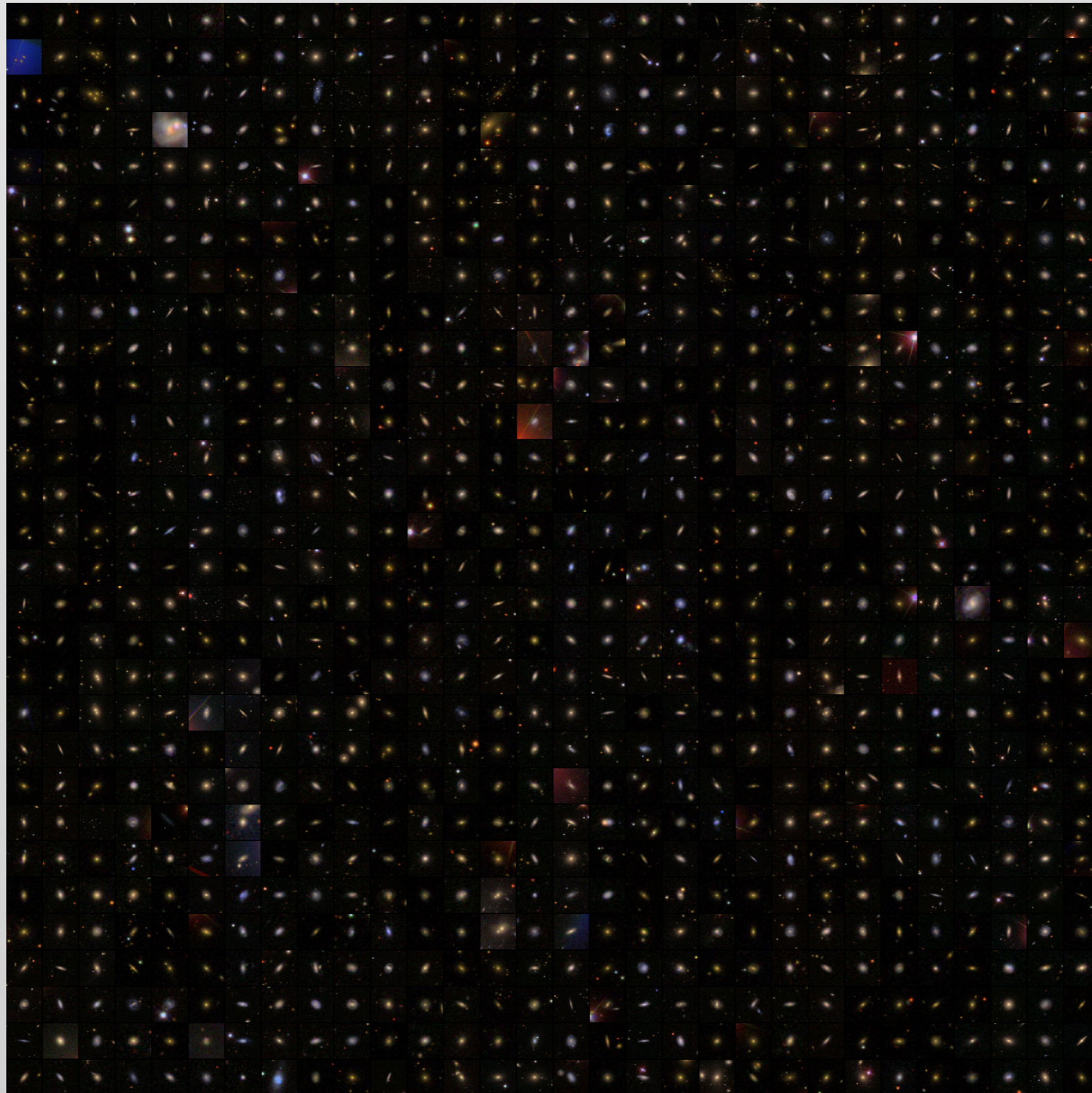


# Automatic cosmic web segmentation

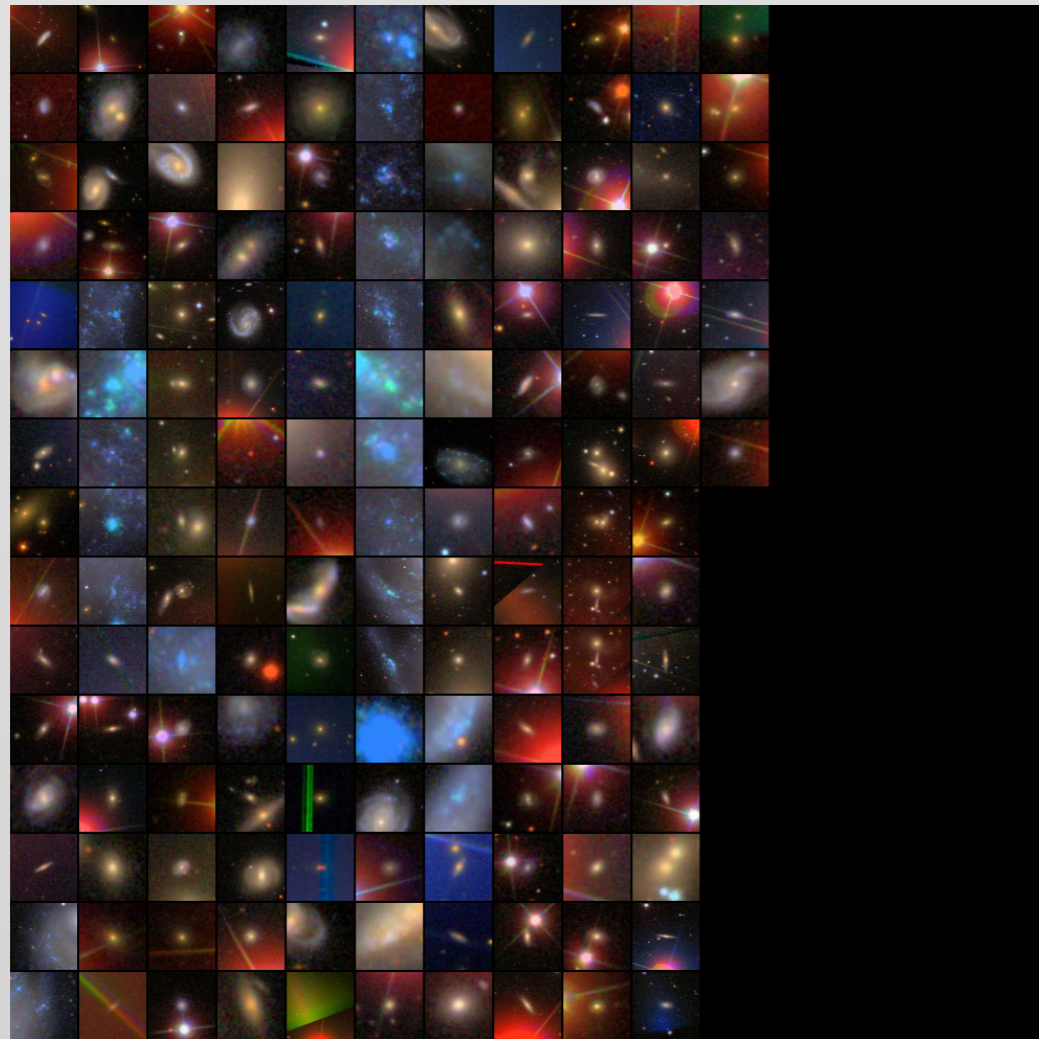


Aragon-Calvo 2019

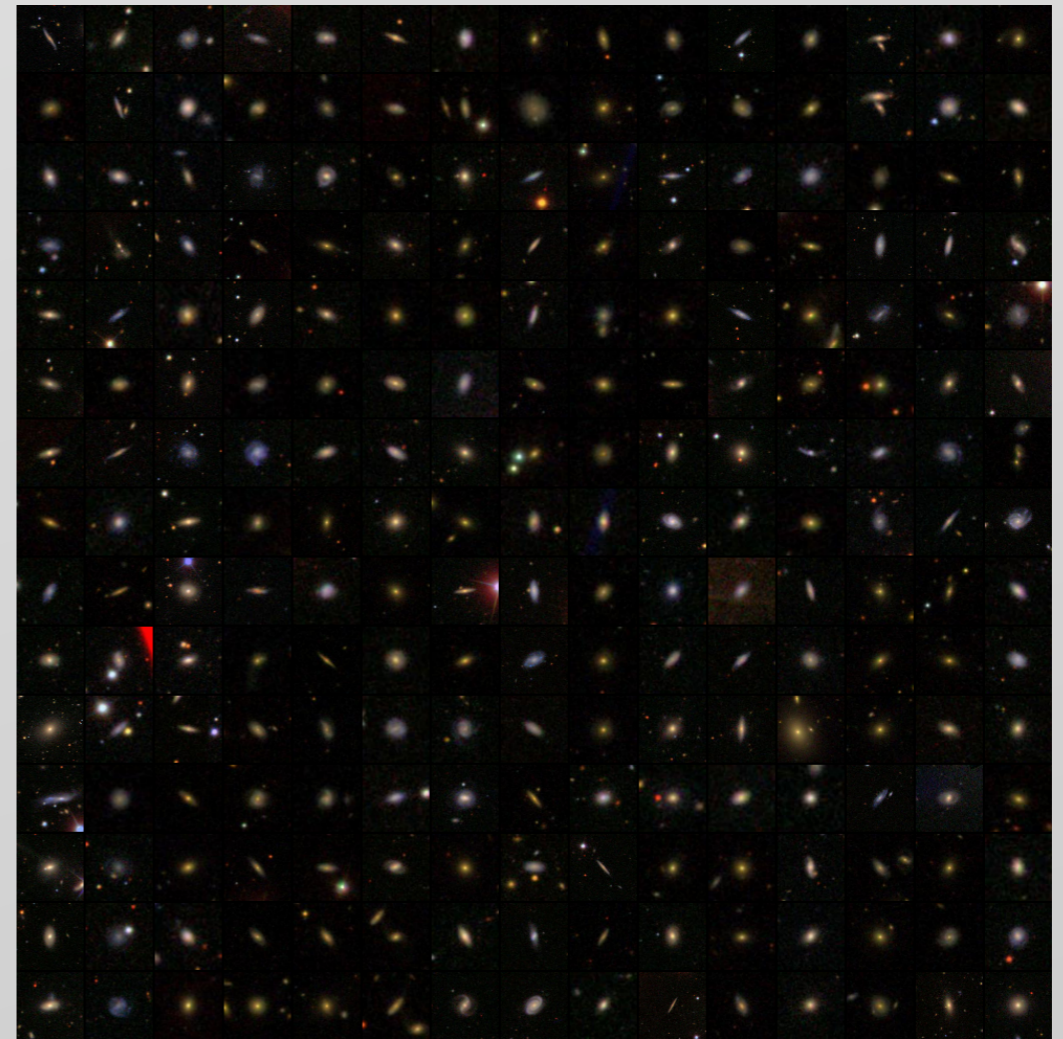
# Automatic selection of bad images



# Automatic selection of bad images

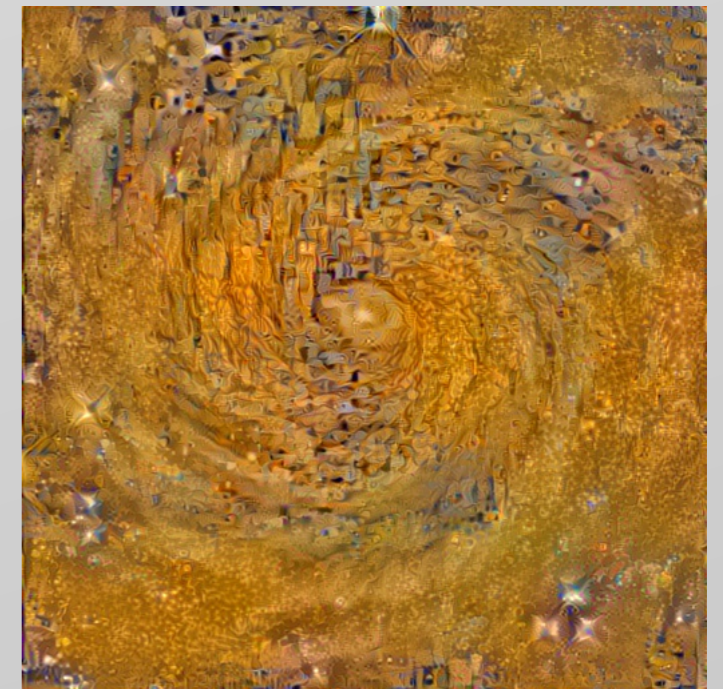
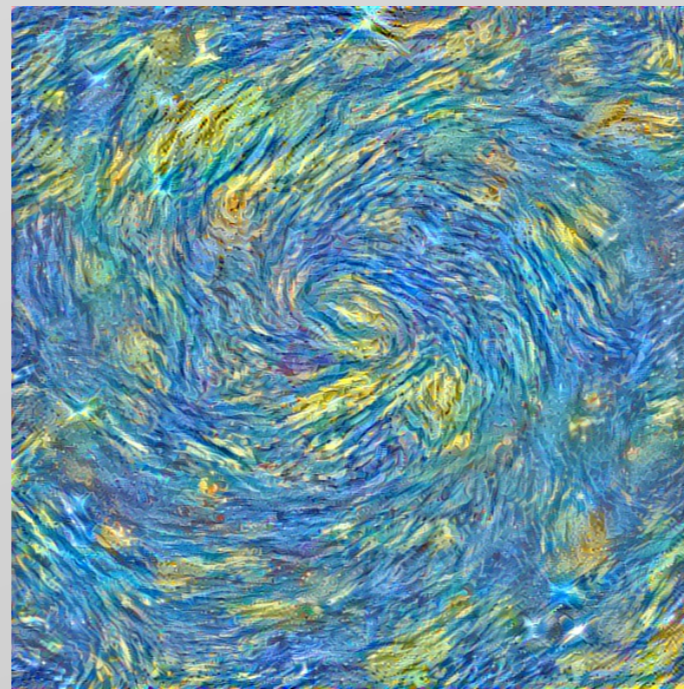
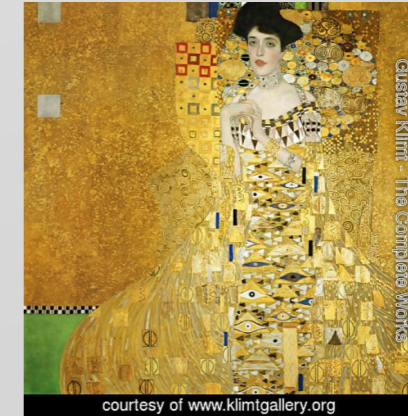


Failed sample

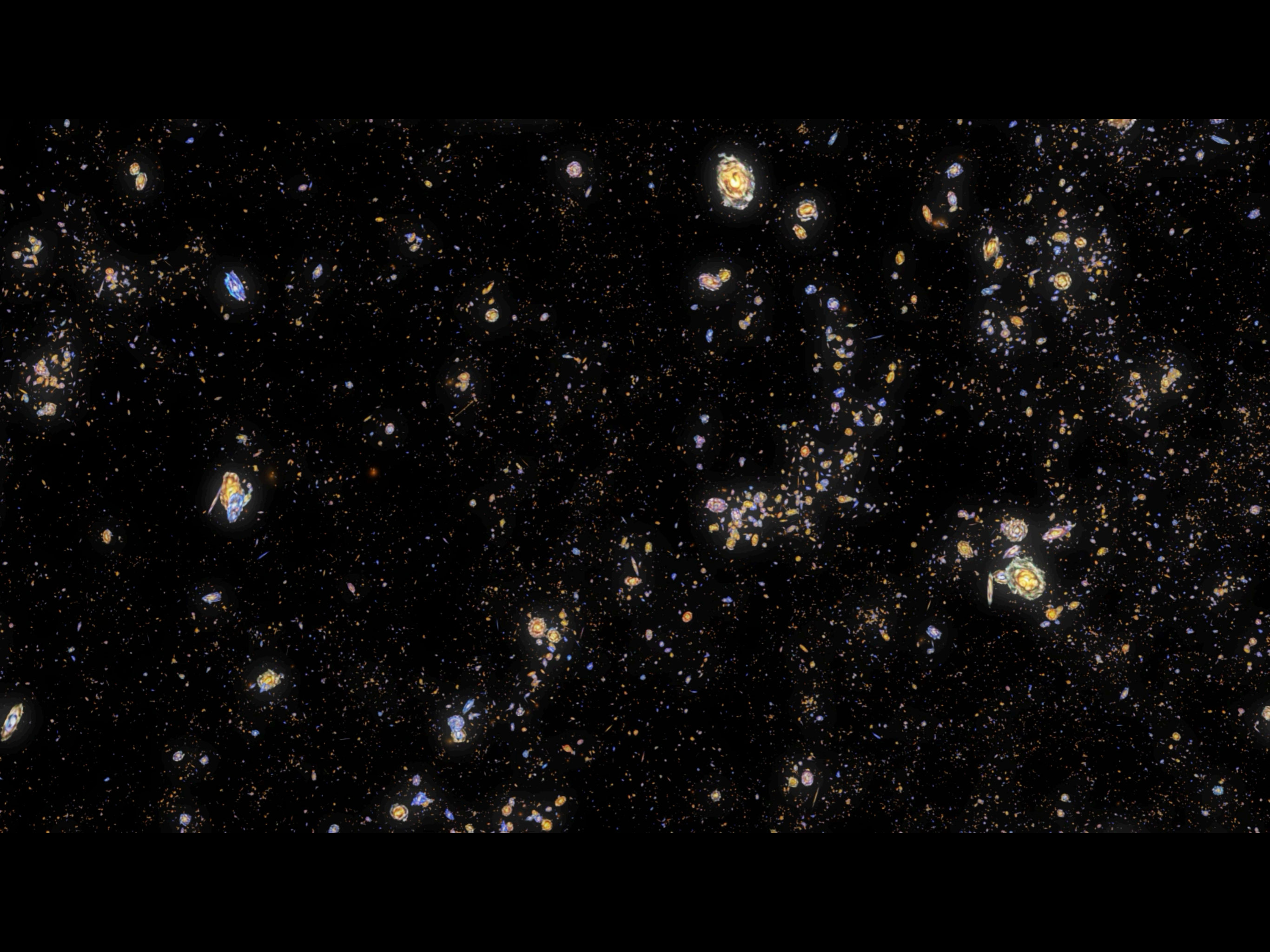


Clean sample

Also not-so serious applications...

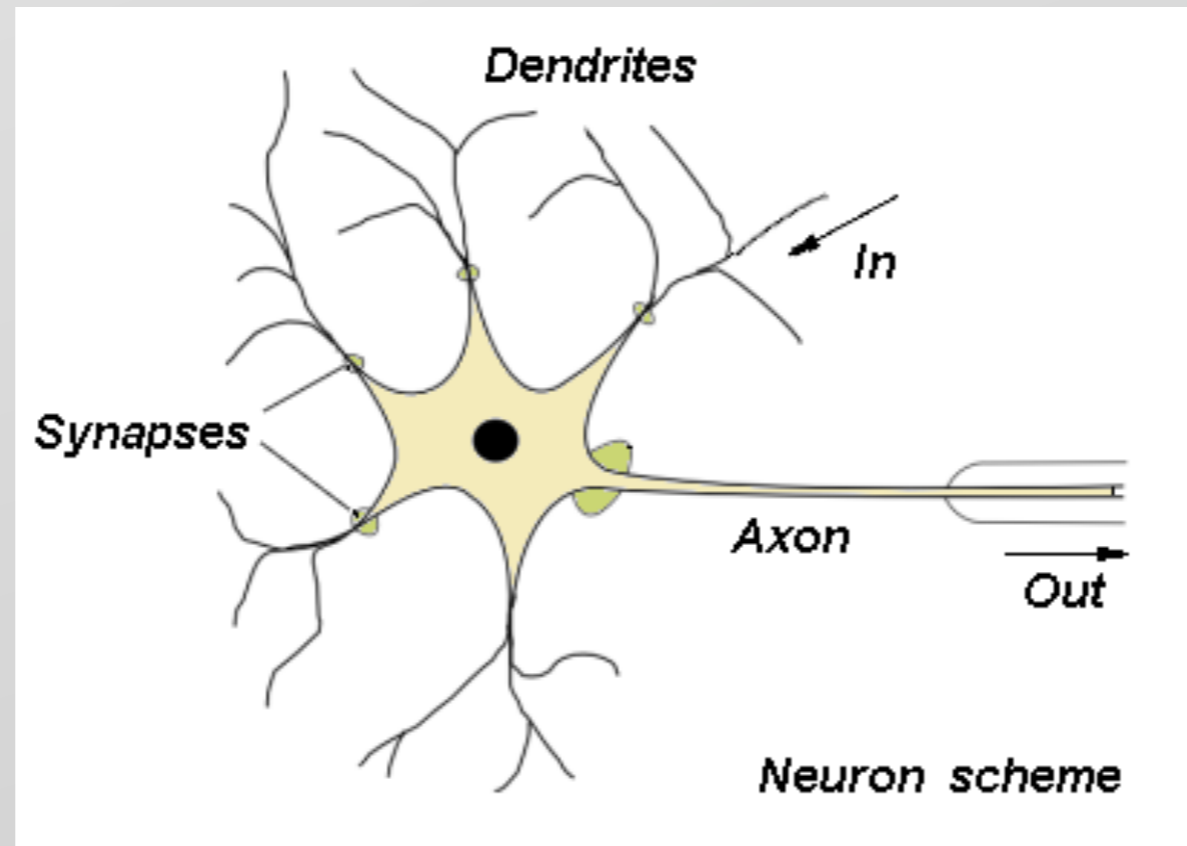


Style transfer



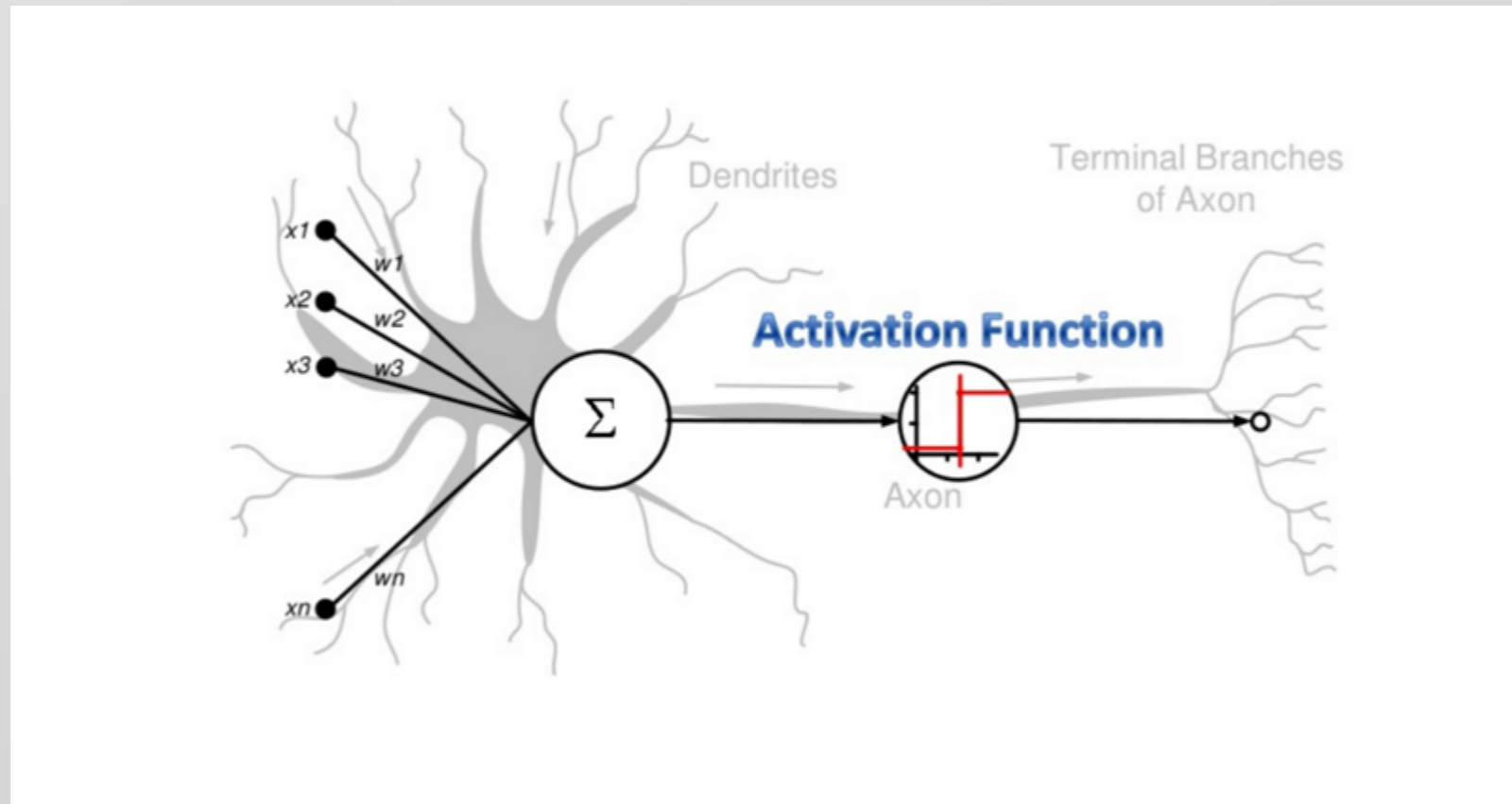
What is an artificial neuron?

2 mins intro...

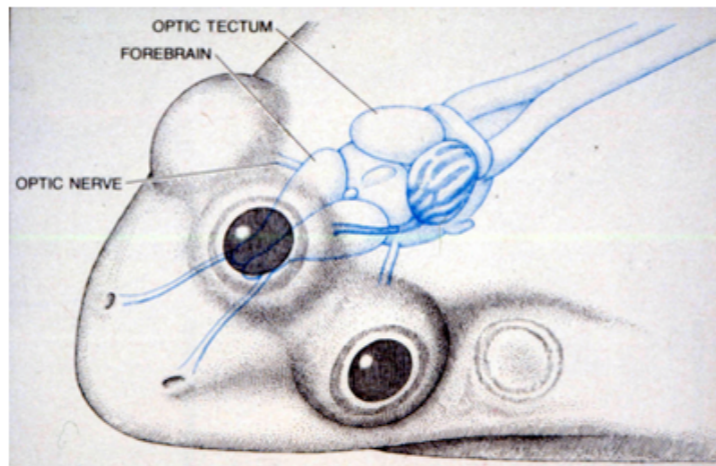


Biological neuron

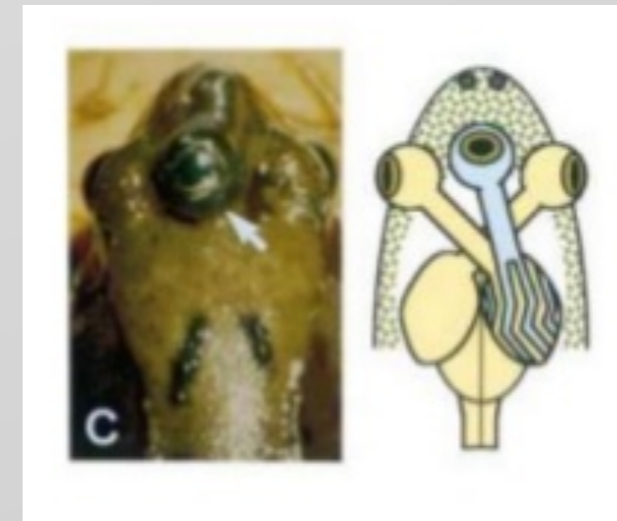
What is an artificial neuron?



Perceptron

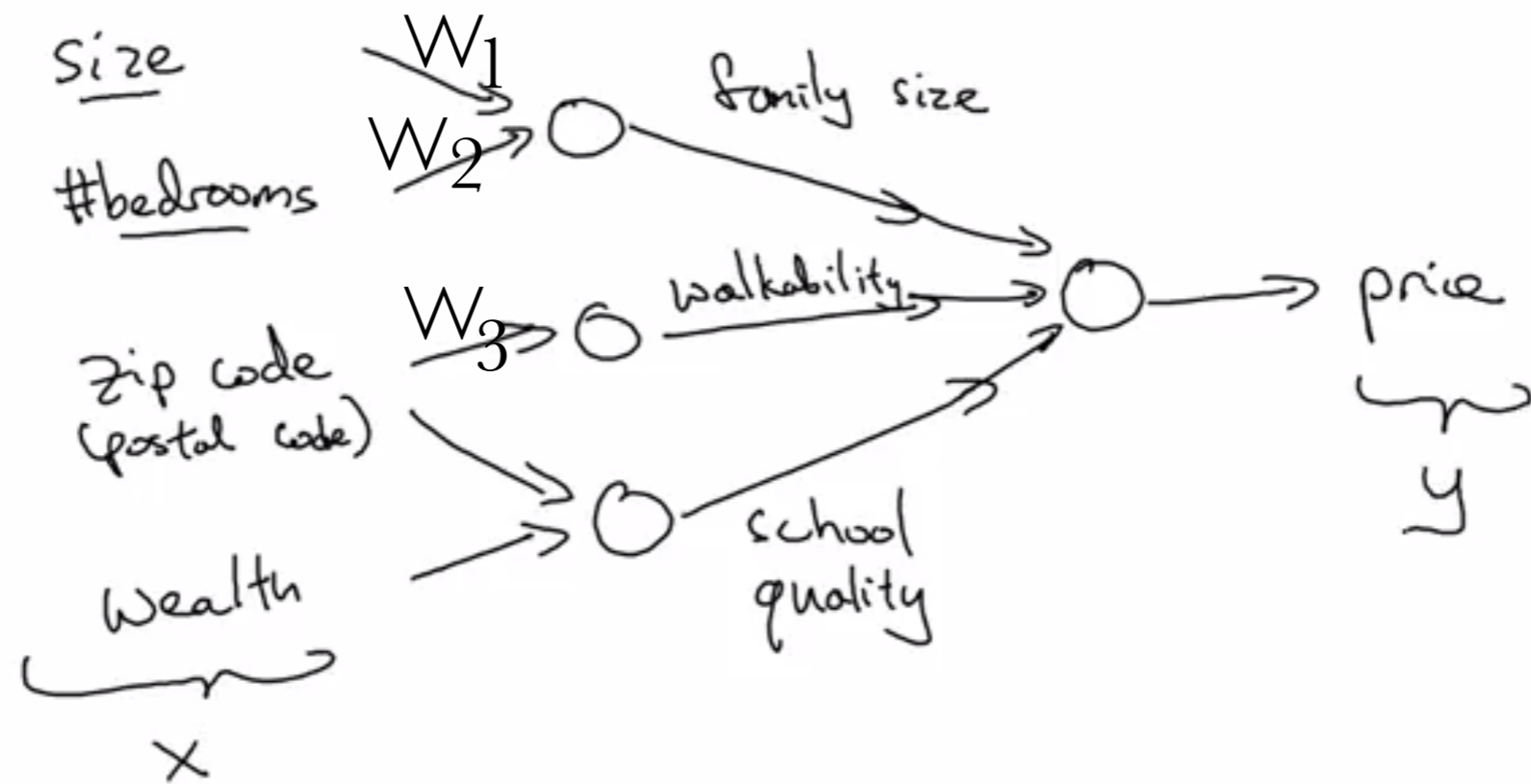


Ocular dominance columns in the optic tectum can be induced in frogs by implantation of a third eye during embryonic development. Normally the retinotectal projection is crossed, but implantation of a third eye results in competition between the third eye and the established eye for tectal target space. Formation of the columns is activity dependent. This experiment supports both the notion that brain wiring is both dependent on molecular cues and on neural activity.

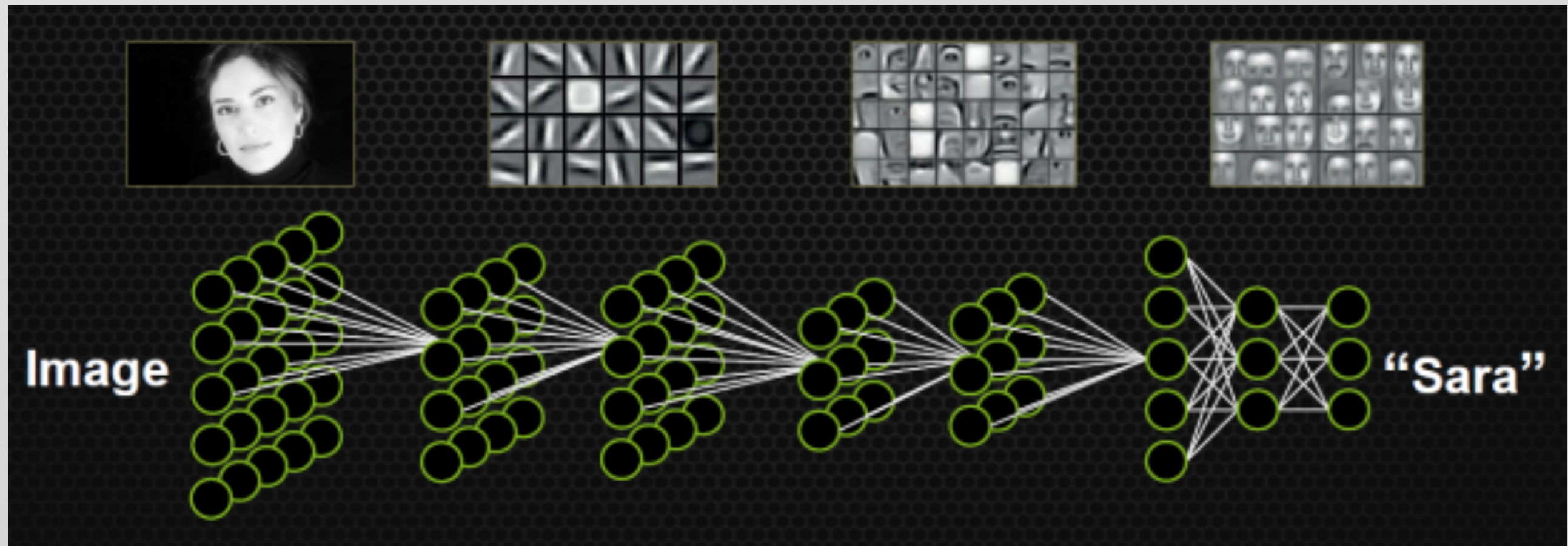


Universal learning algorithm?





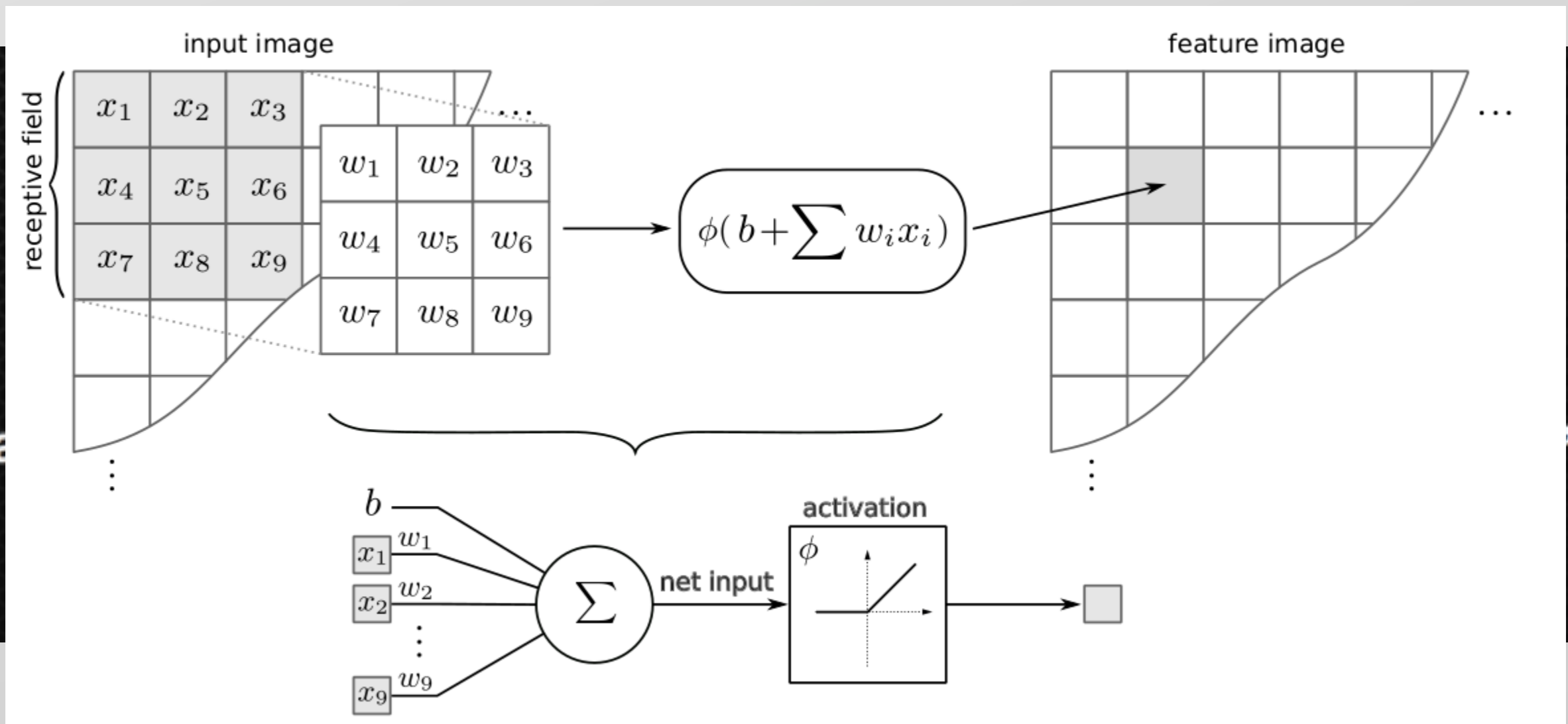
# Deep Learning



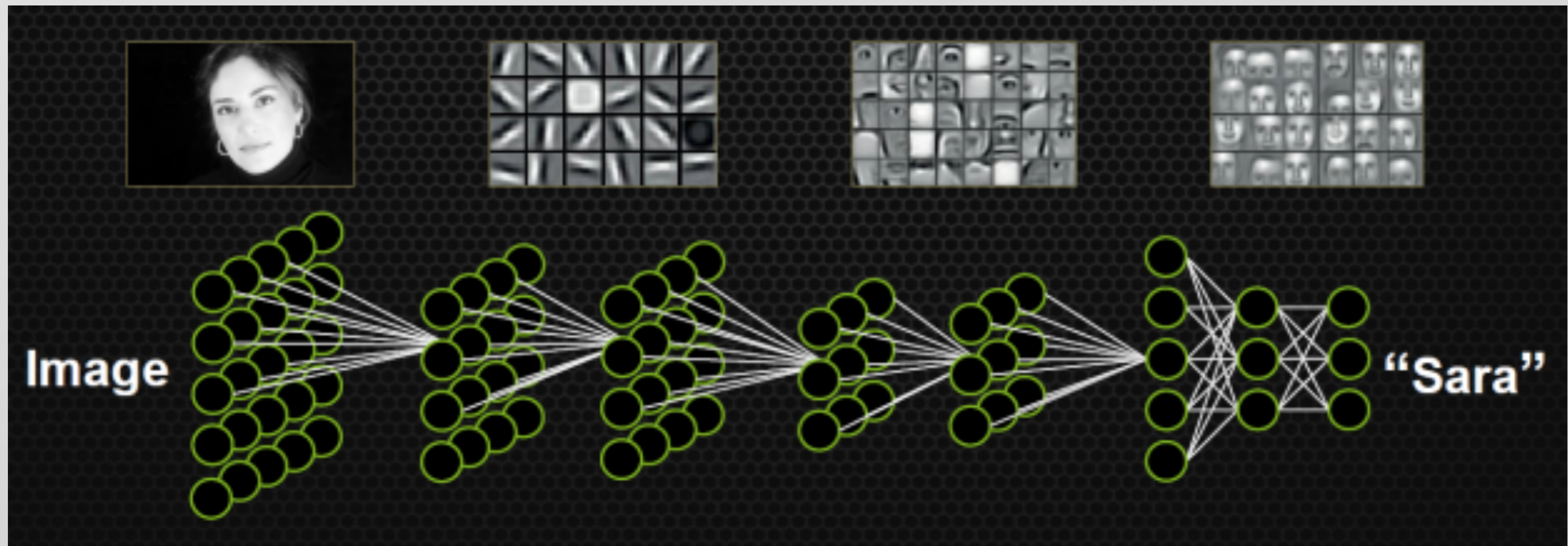
Resolution  
←

Abstraction  
→

# Deep Learning



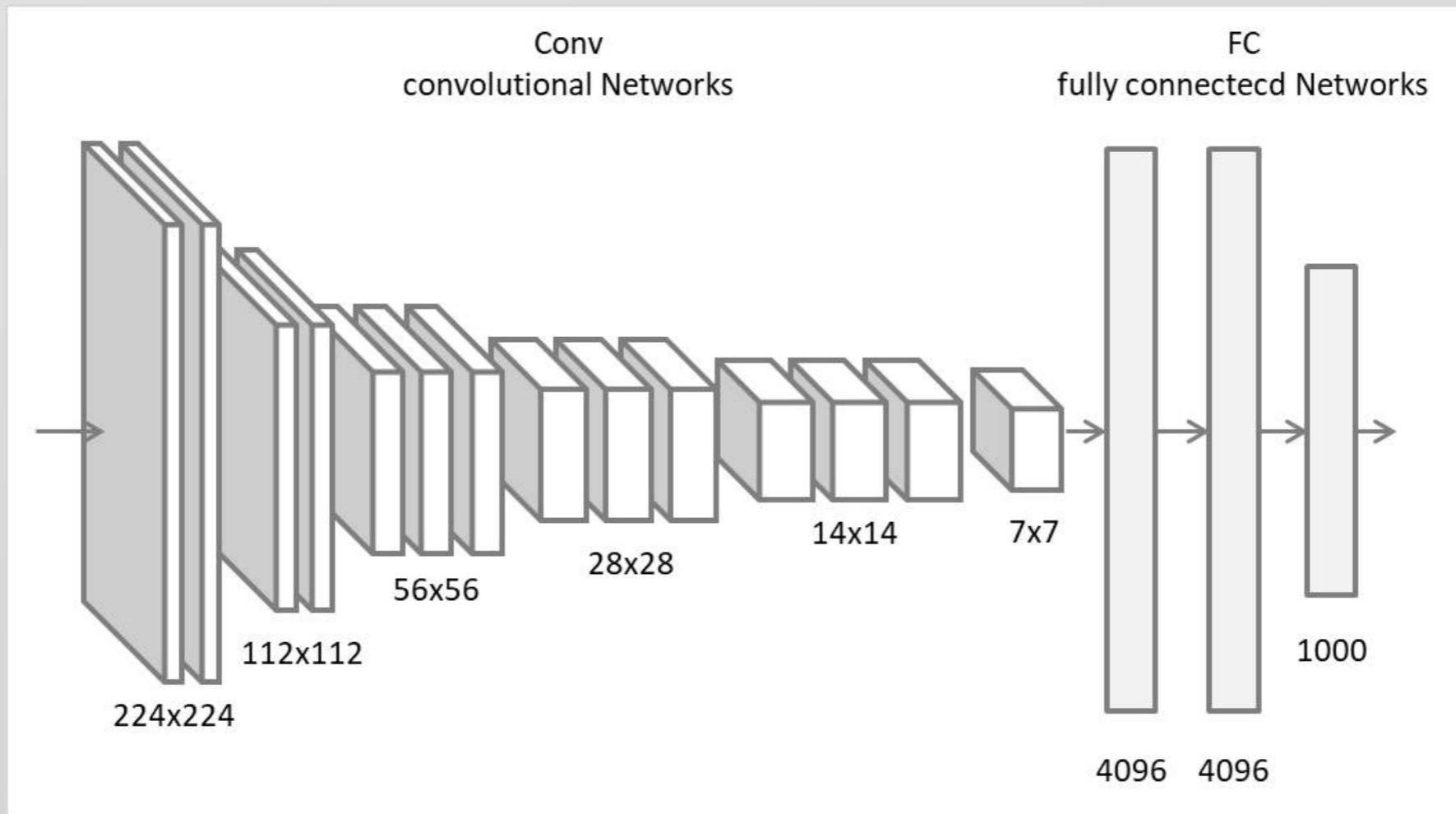
# Deep Learning



Feature extractor

Aggregator

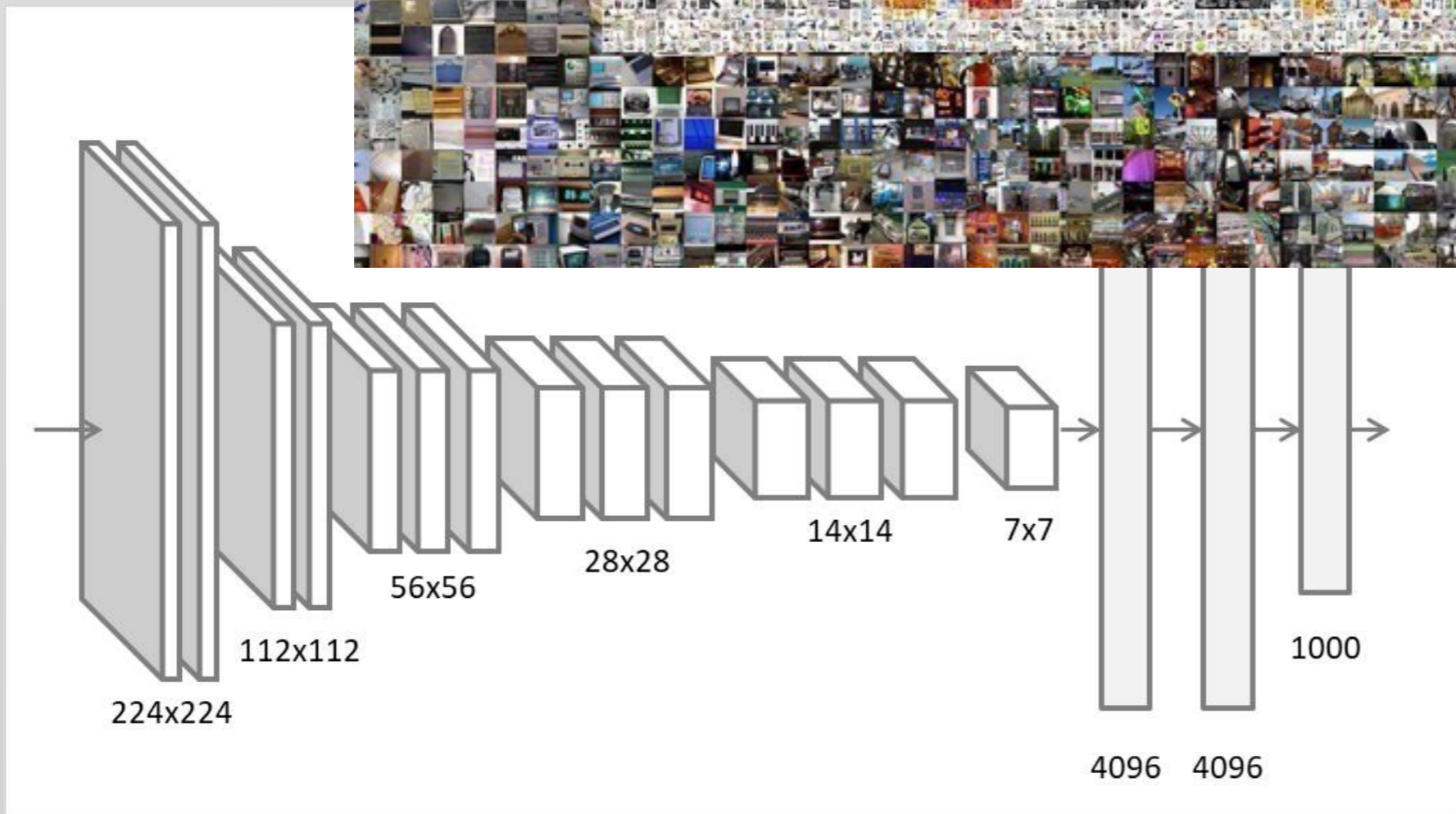
# VGG16 (2014)



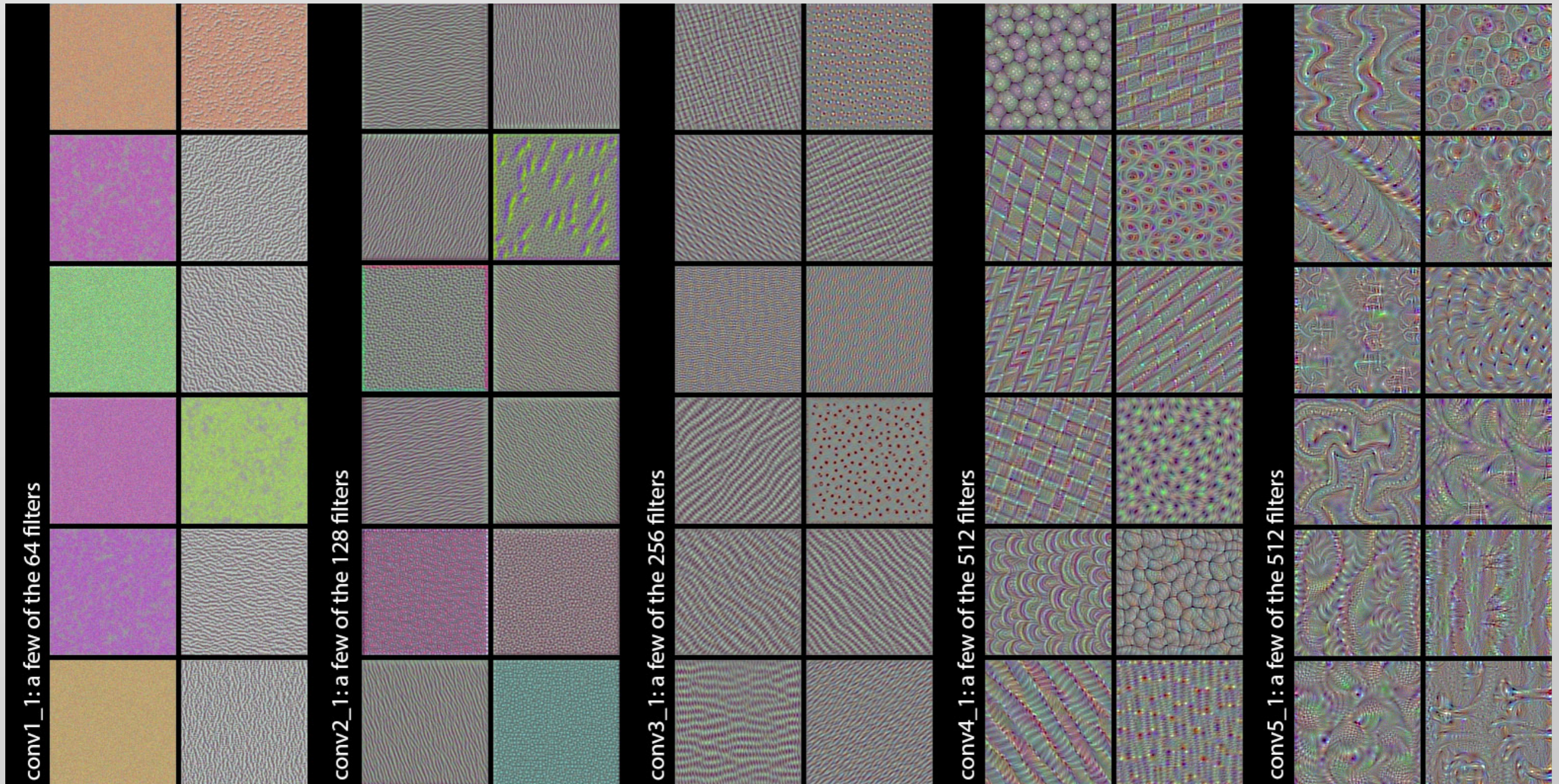
Feature Extractor

Aggregator

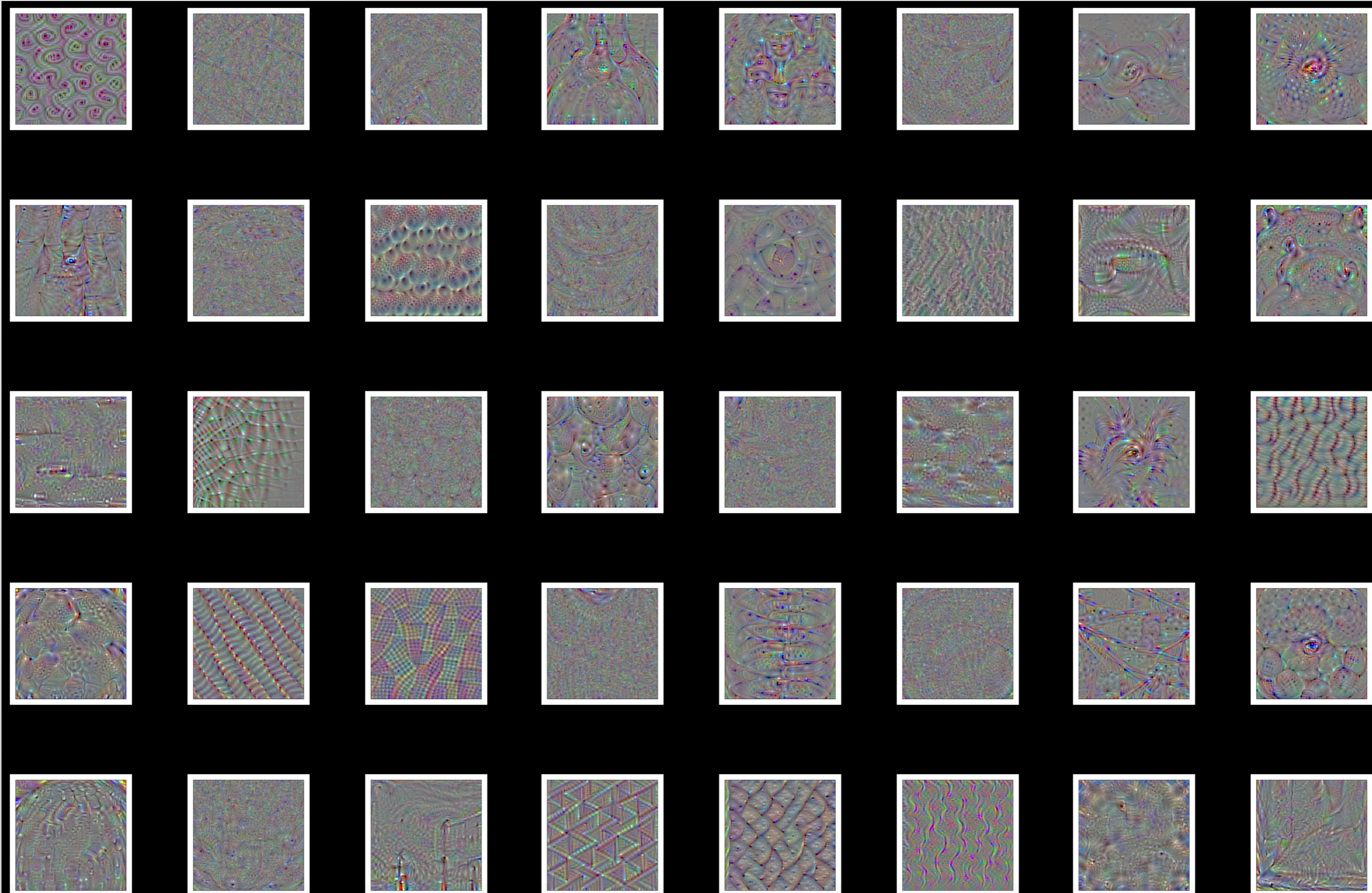
# VGG16 (2014)



# VGG16 filters trained on ImageNet

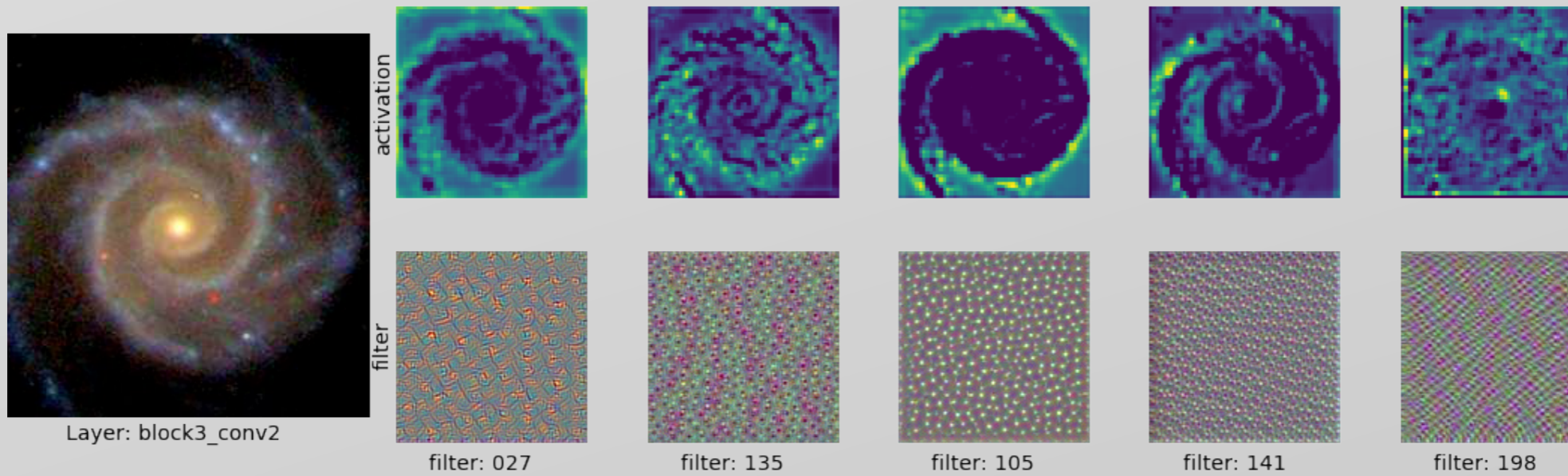
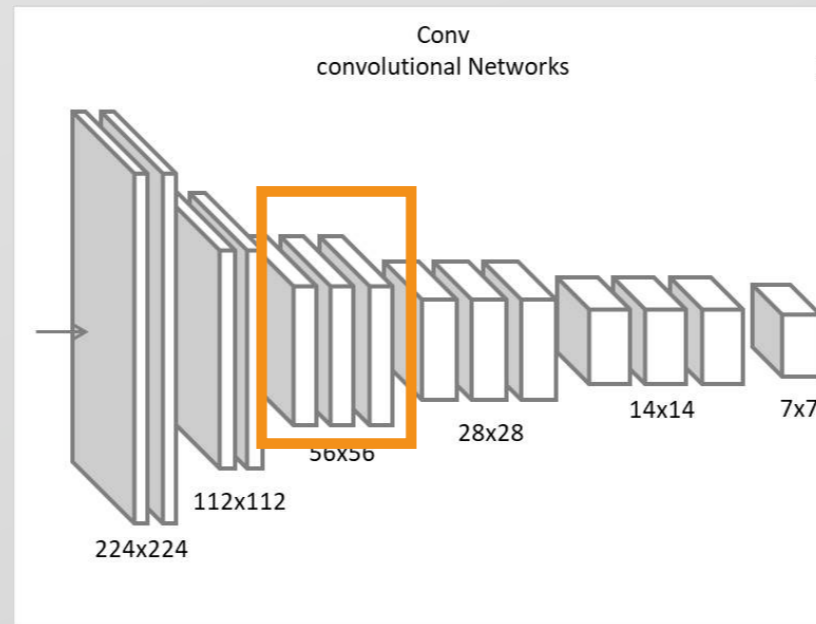


# VGG16, some filters in last convolutional layer (5 | 2)

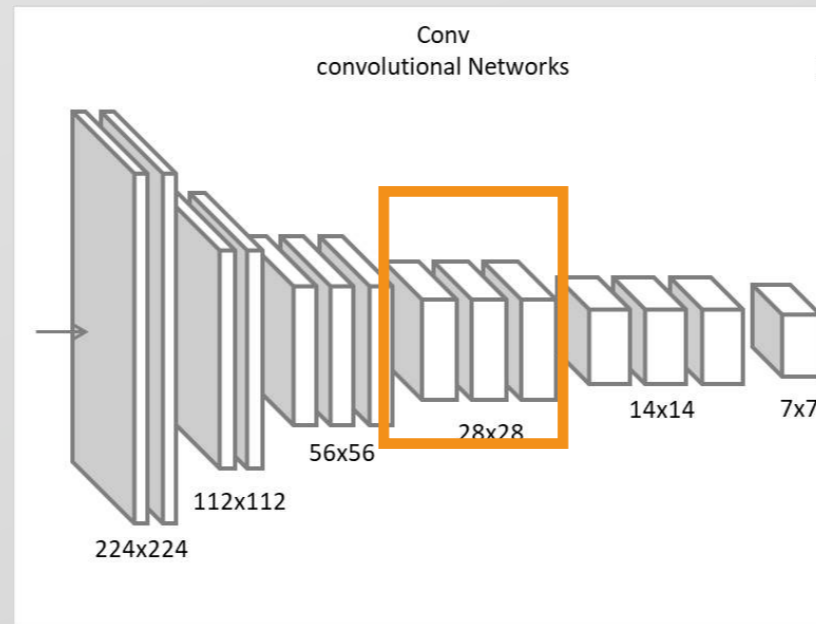




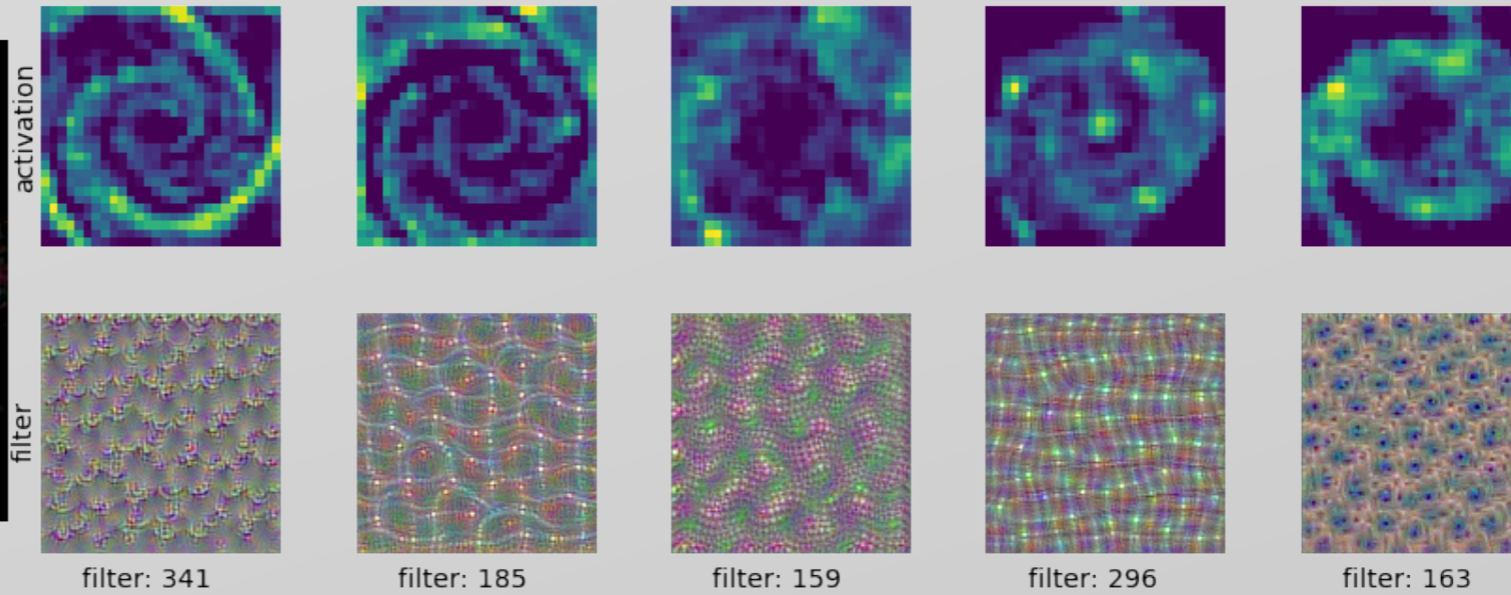
# How do neural nets see the world?



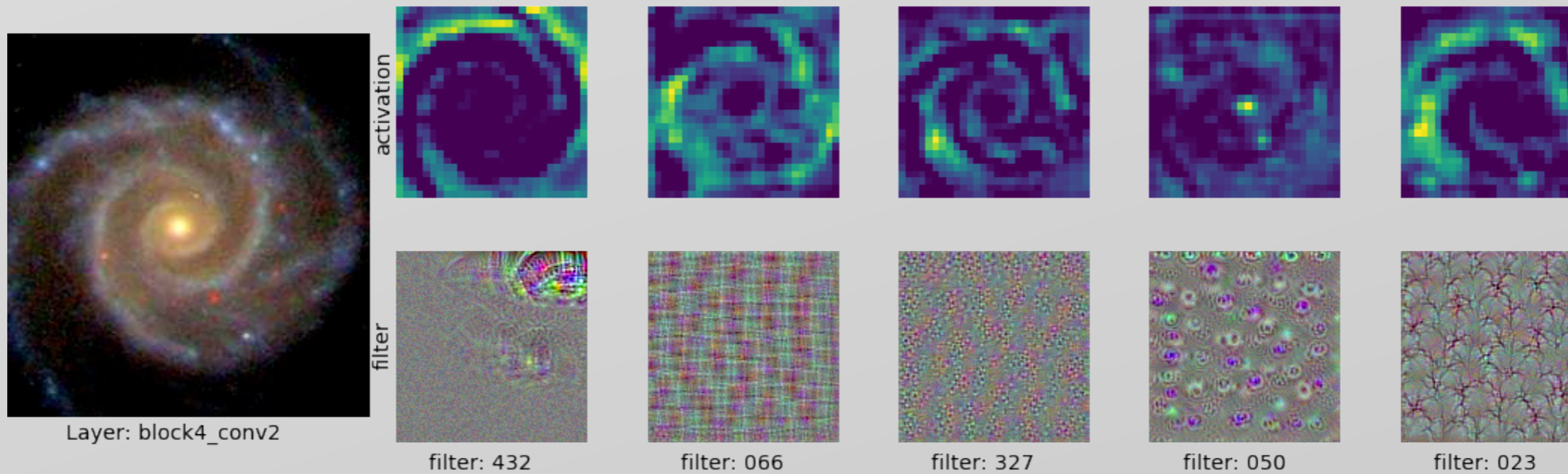
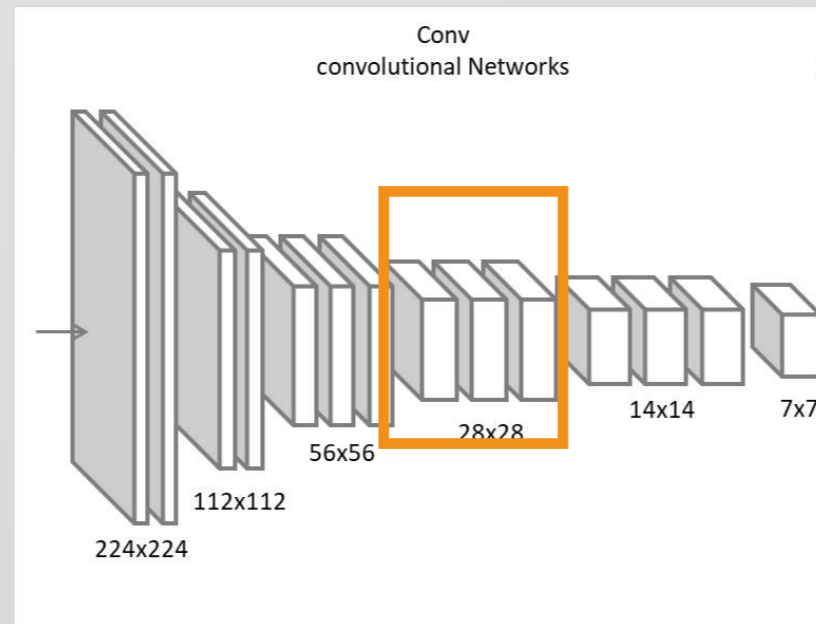
# How do neural nets see the world?



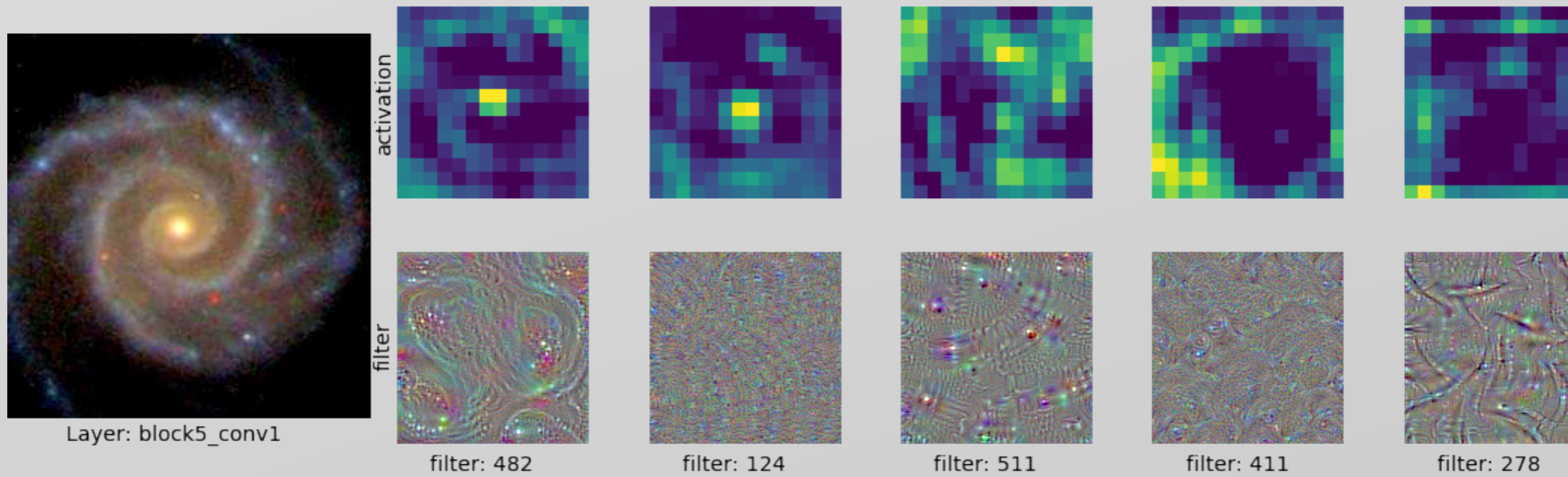
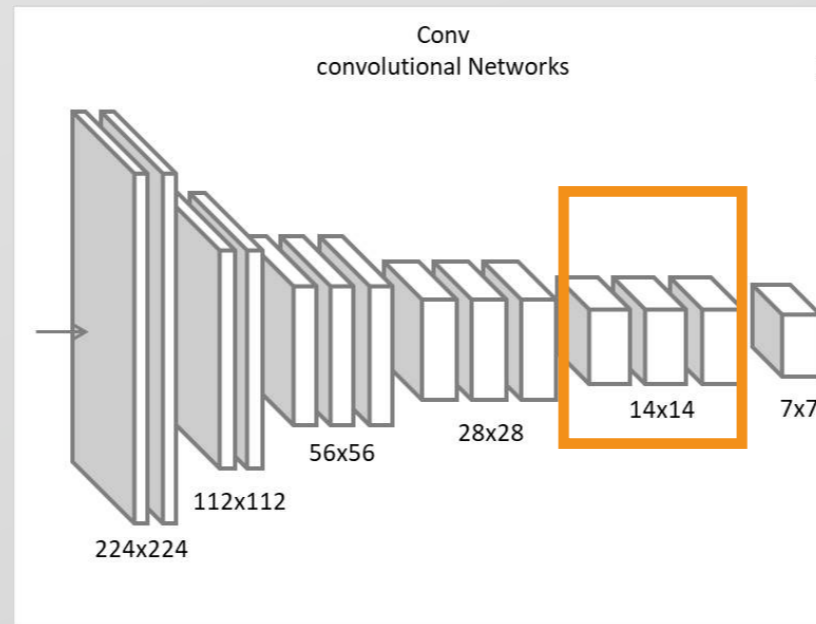
Layer: block4\_conv1



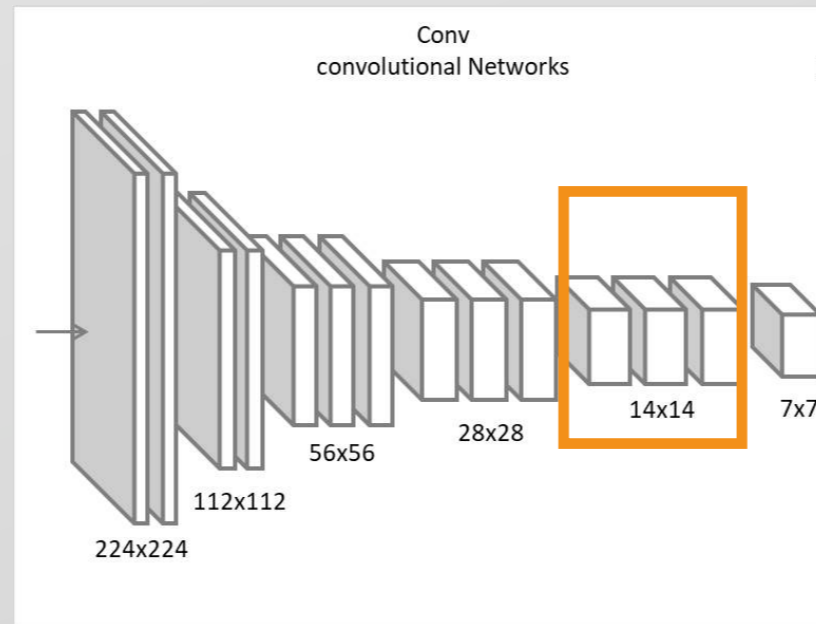
# How do neural nets see the world?



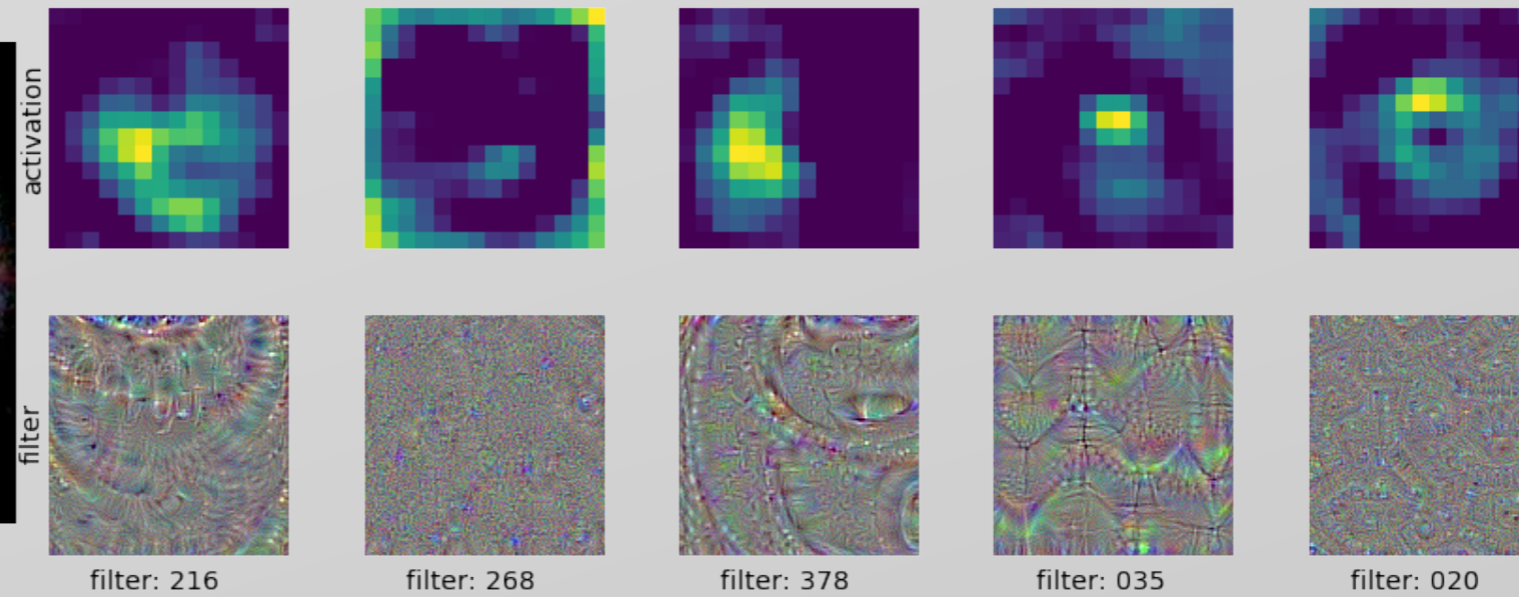
# How do neural nets see the world?



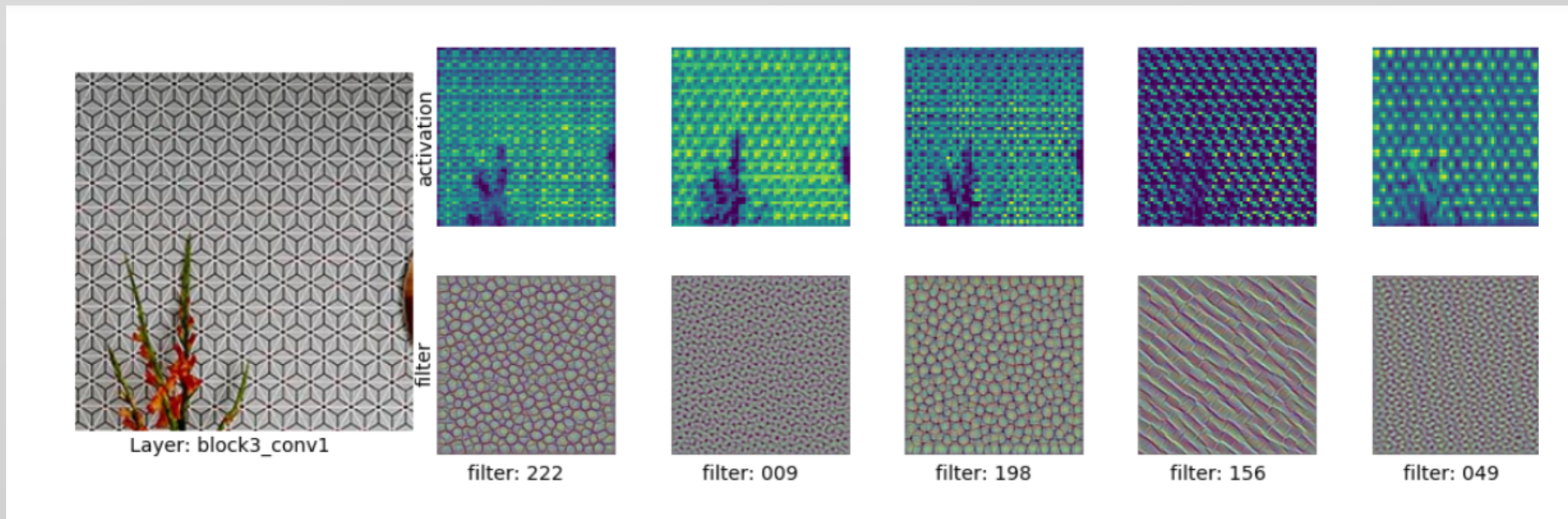
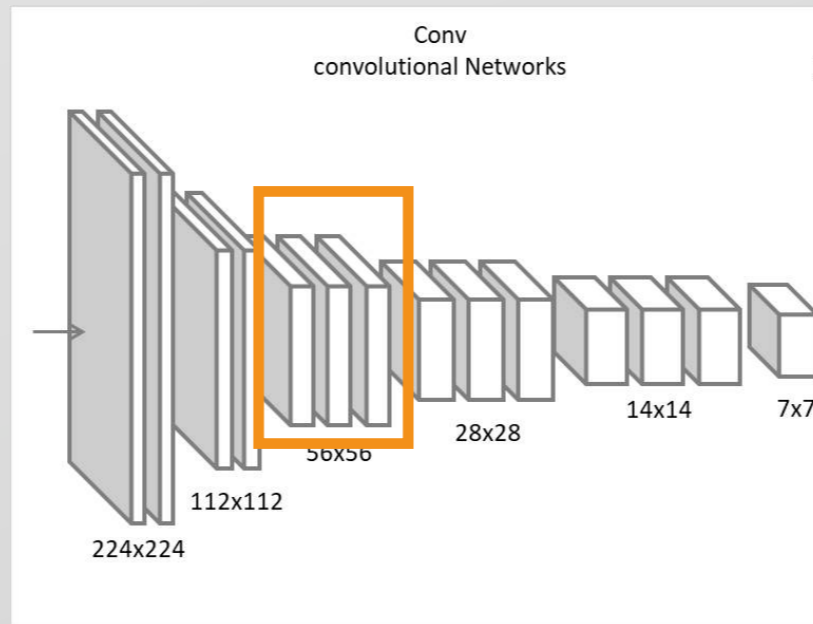
# How do neural nets see the world?



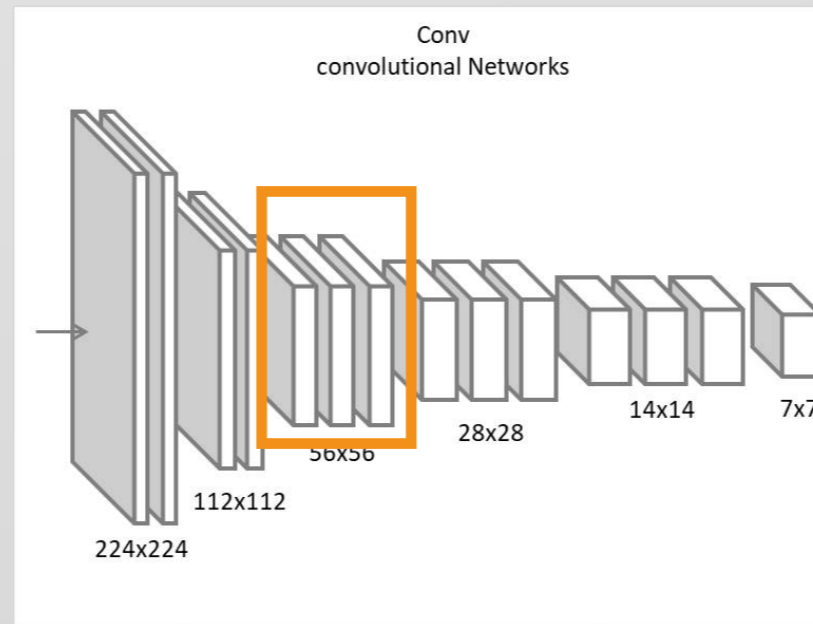
Layer: block5\_conv2



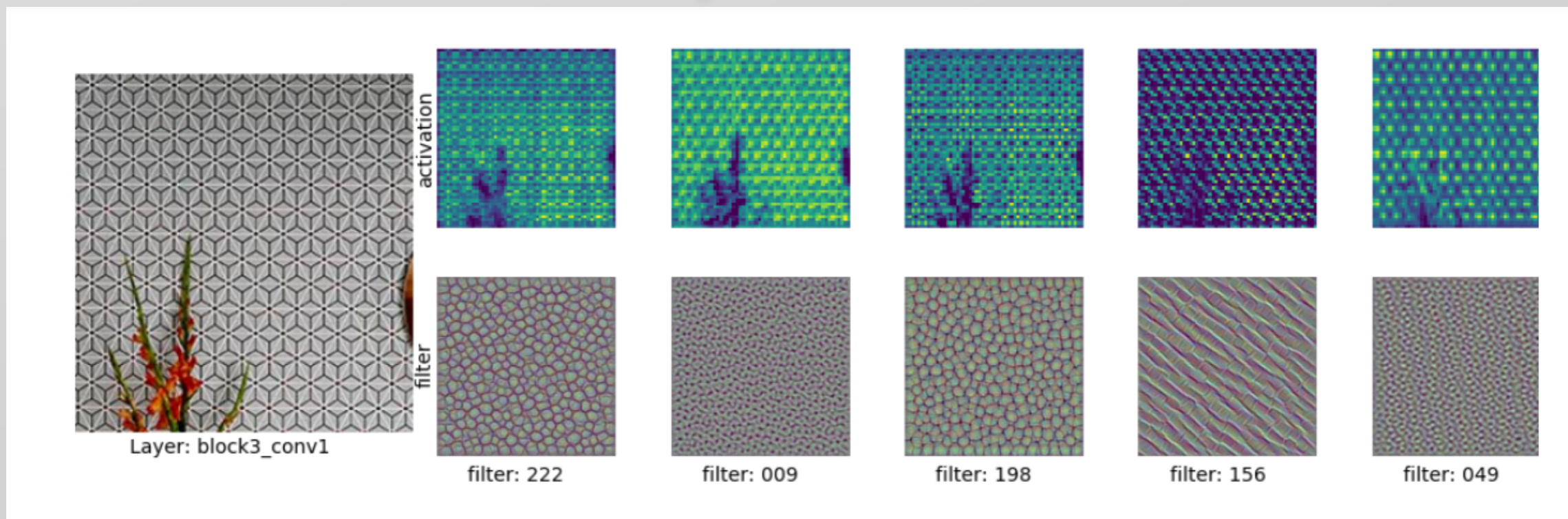
# How do neural nets see the world?



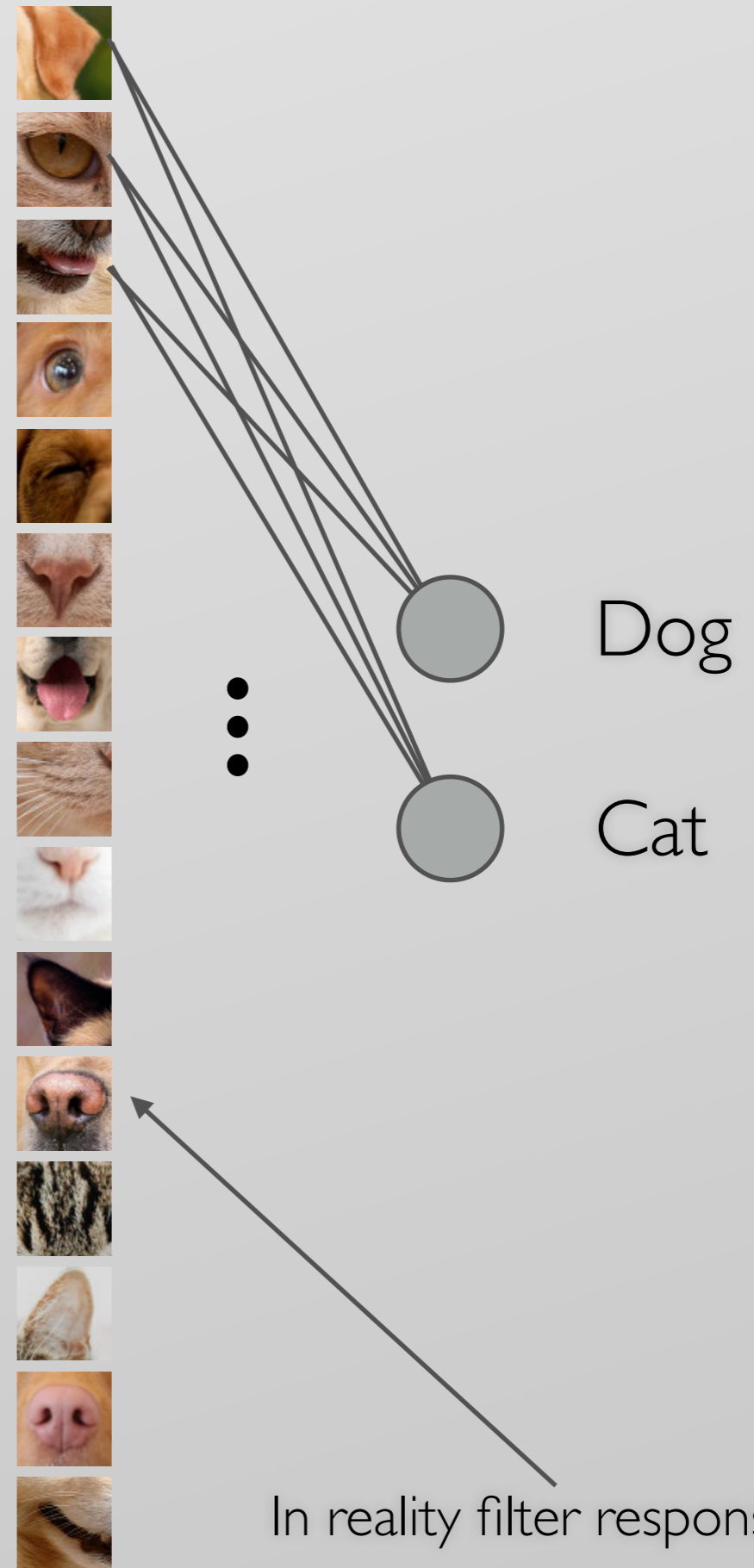
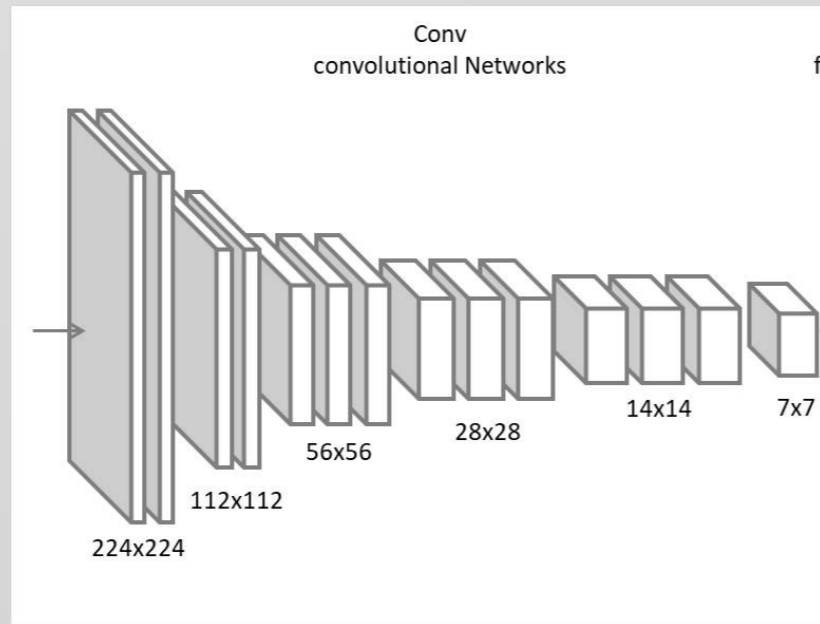
# How do neural nets see the world?



## How do they make decisions?

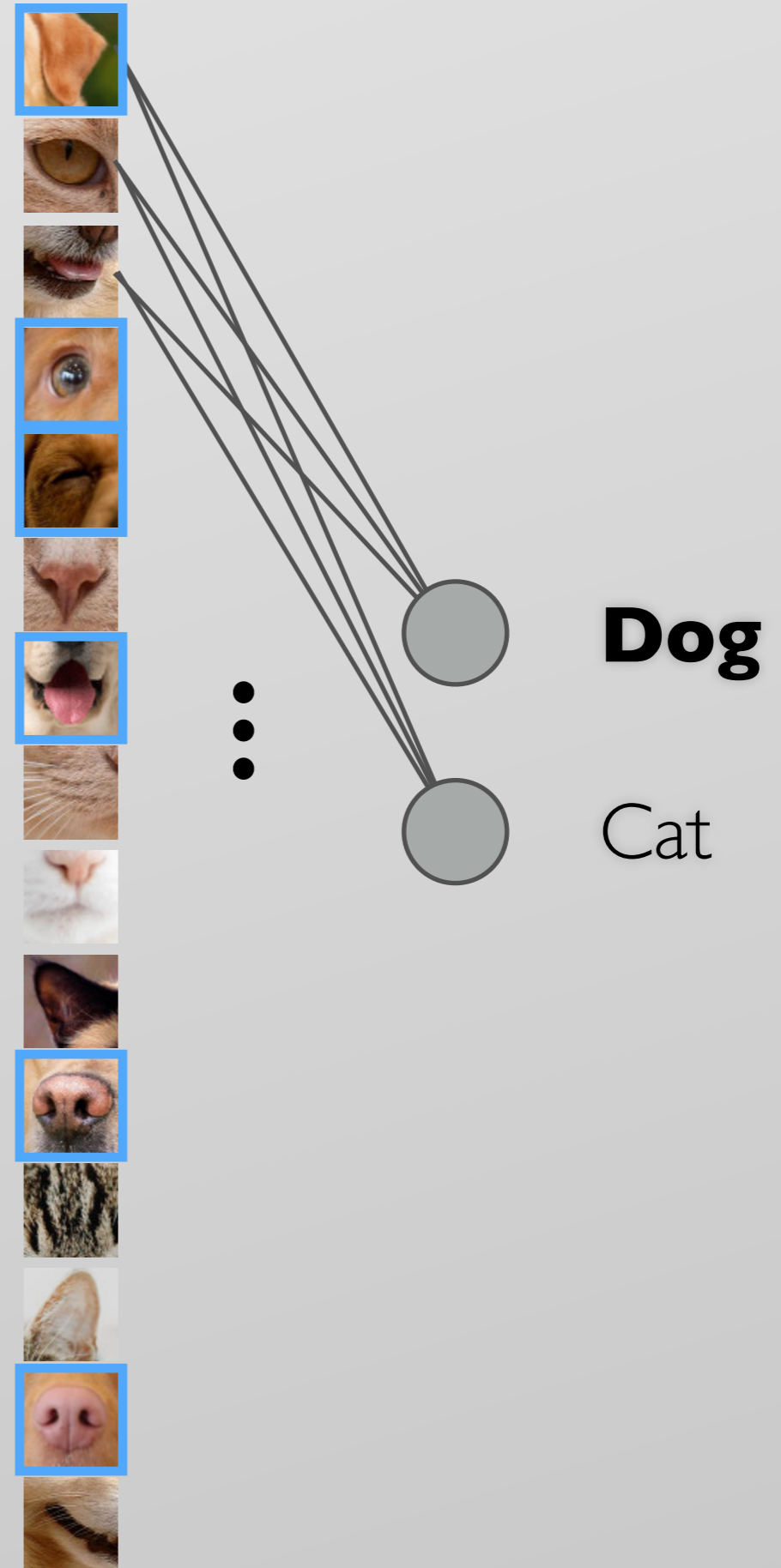
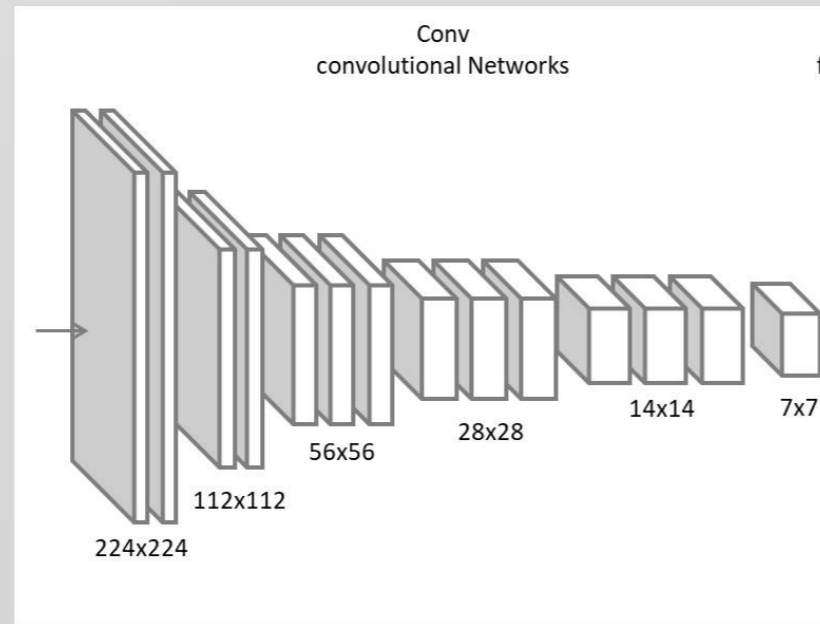


# Deep Neural Nets

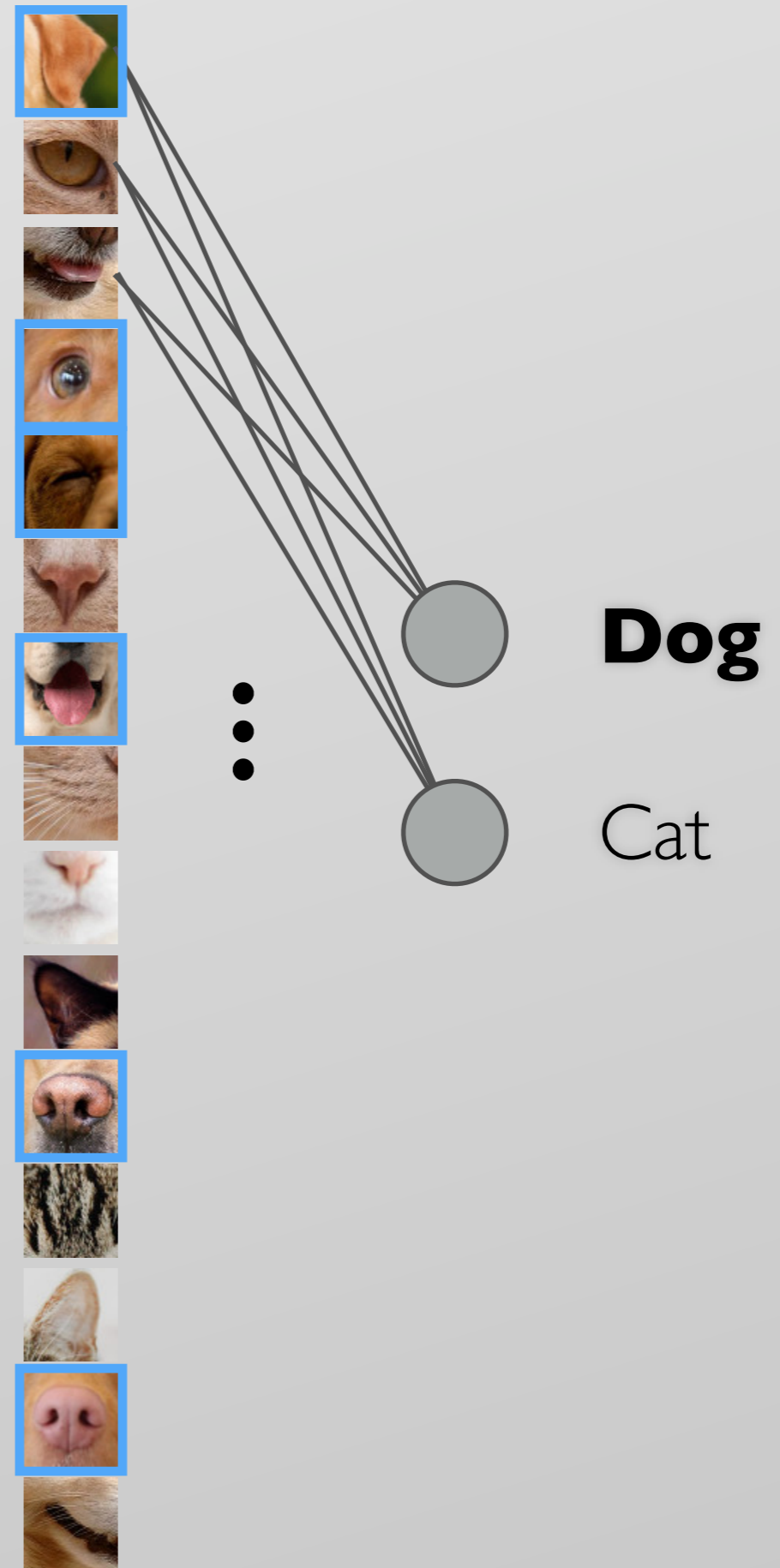
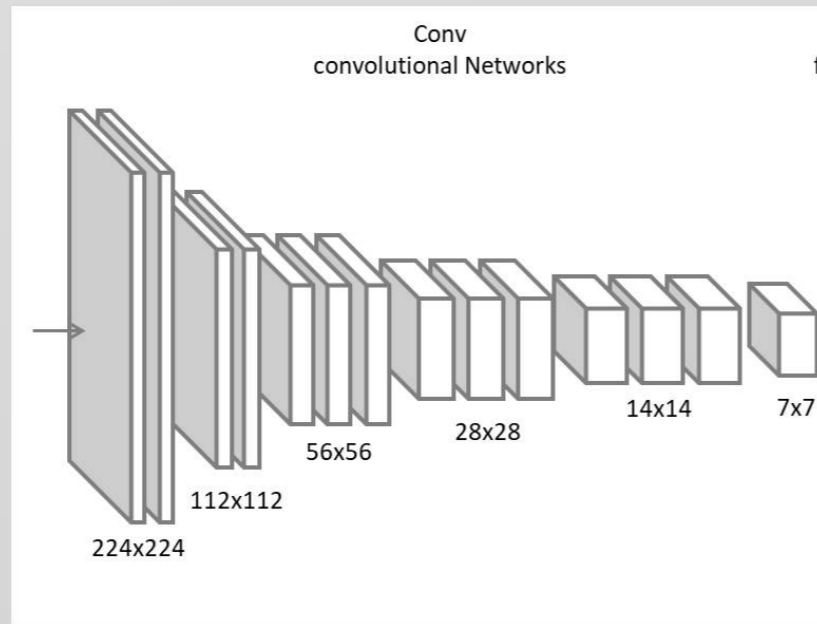




# Deep Neural Nets



# Deep Neural Nets



Sparse encoding?

# Sparse encoding

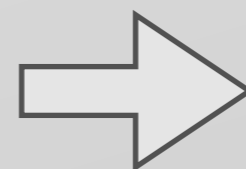
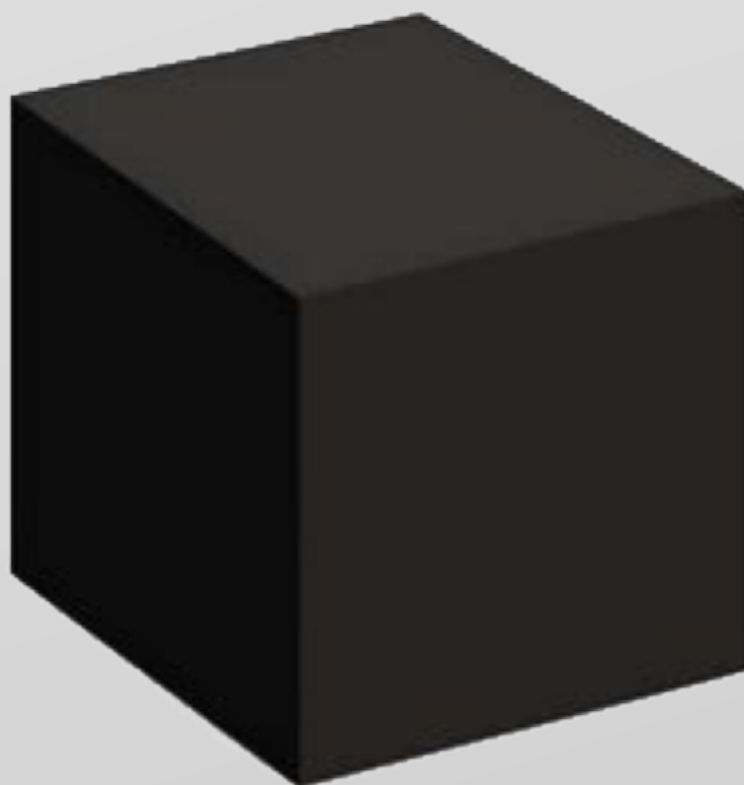
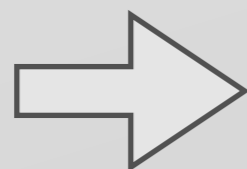
$$I(R) = I_e e^{-7.669 \left[ \left( \frac{R}{R_e} \right)^{1/4} - 1 \right]}$$

de Vaucouleurs profile

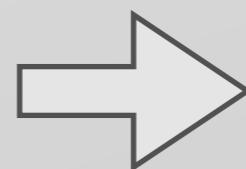
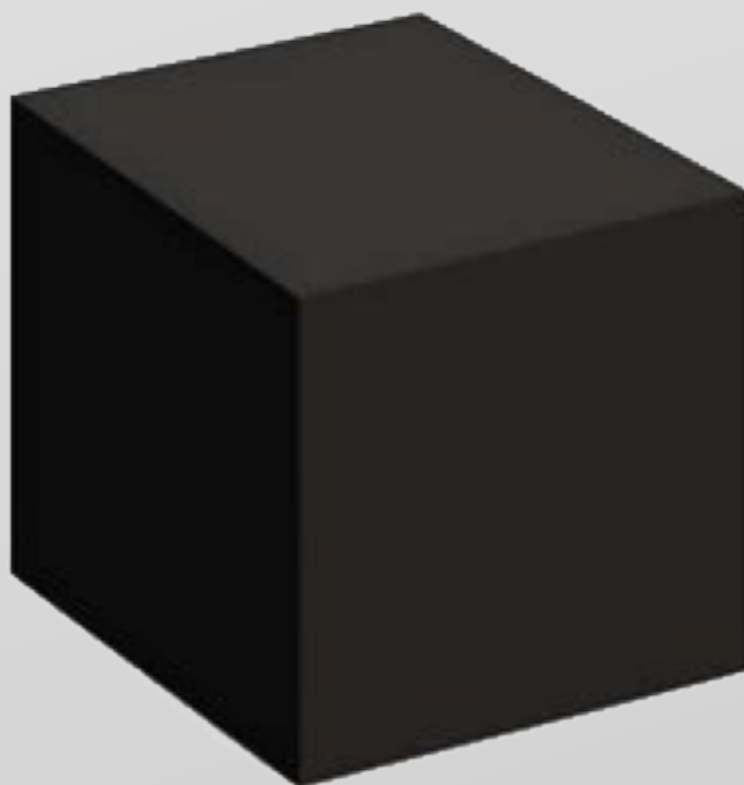
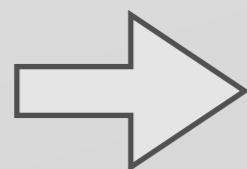


M87

# Deen Neural Nets



**Dog**



What is the problem we want to solve?

Accurate, fast, cheap predictions ?

What is the problem we want to solve?

Accurate, fast, cheap predictions ?

New insight, test new ideas ?

What is the problem we want to solve?

Accurate, fast, cheap predictions ?

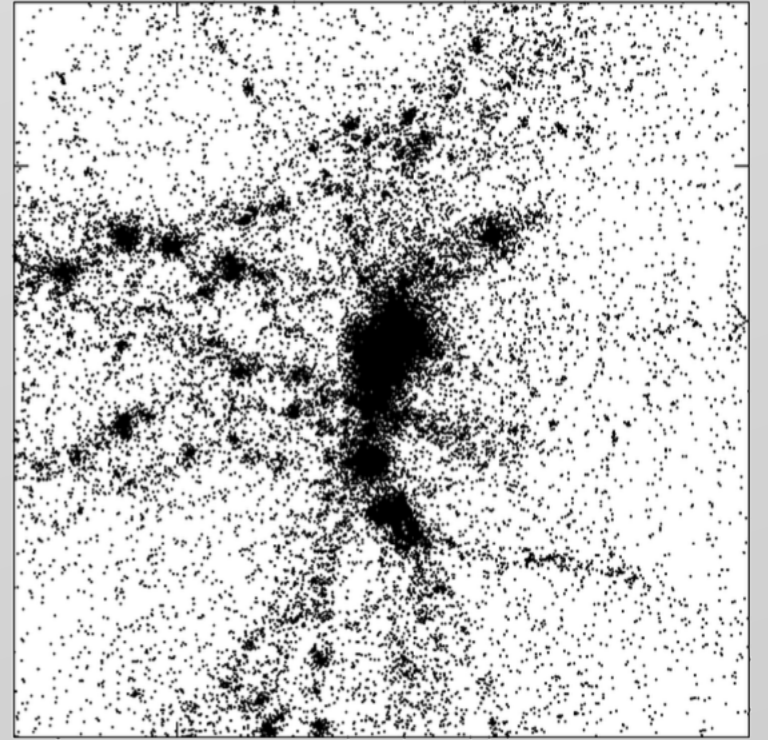
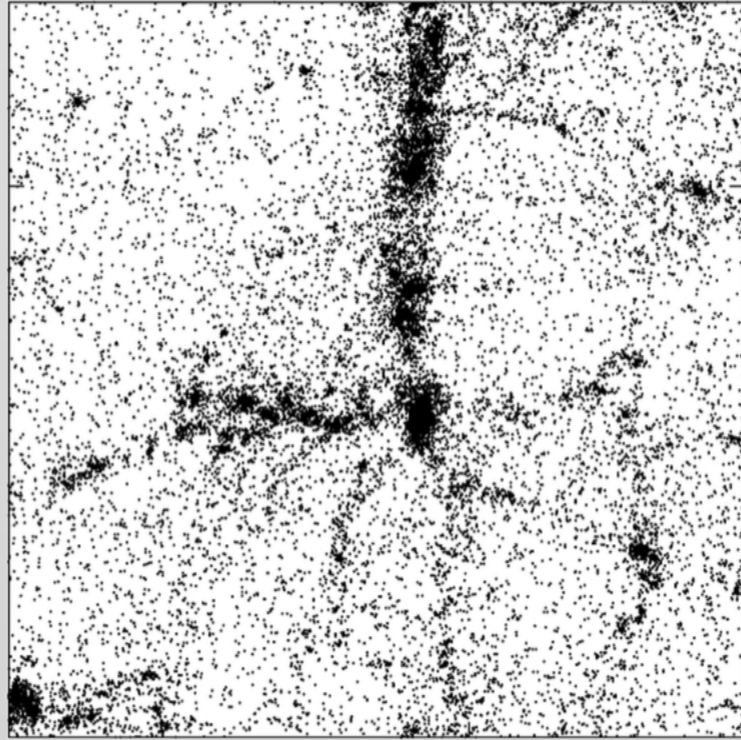
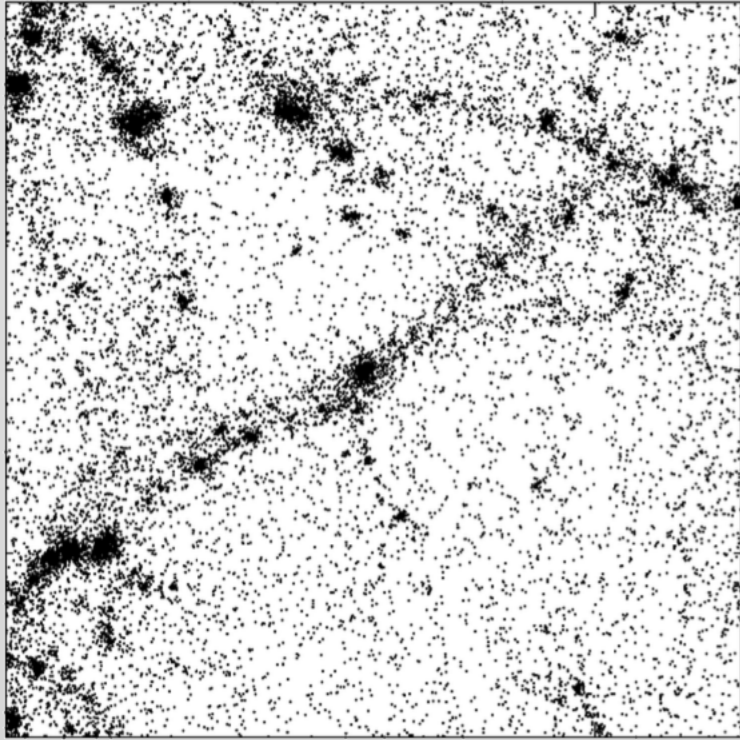
**New insight, test new ideas ?**

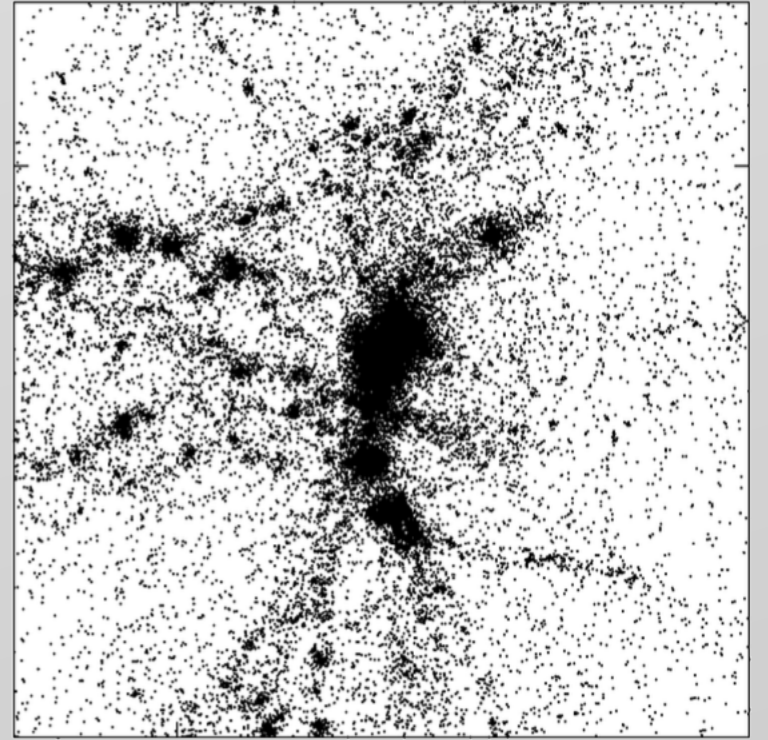
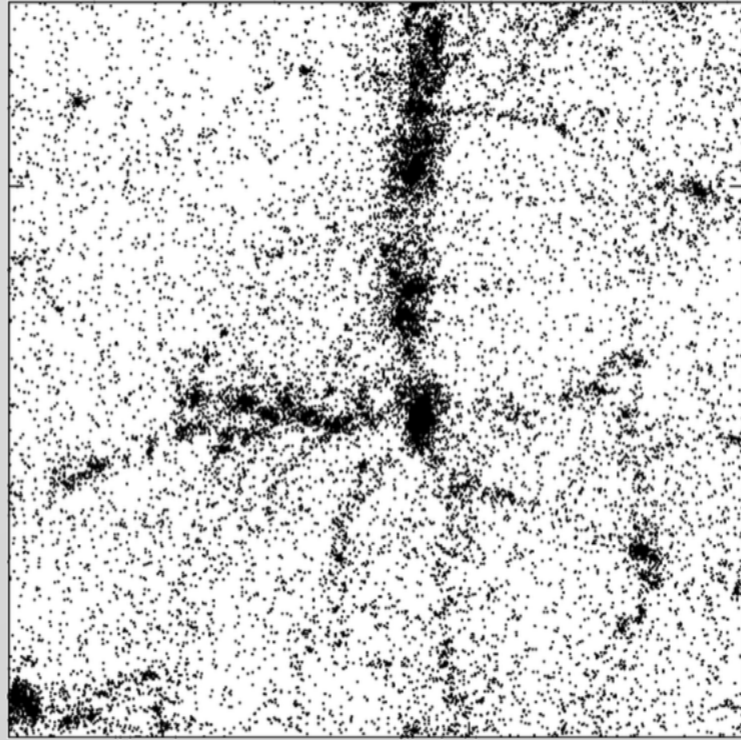
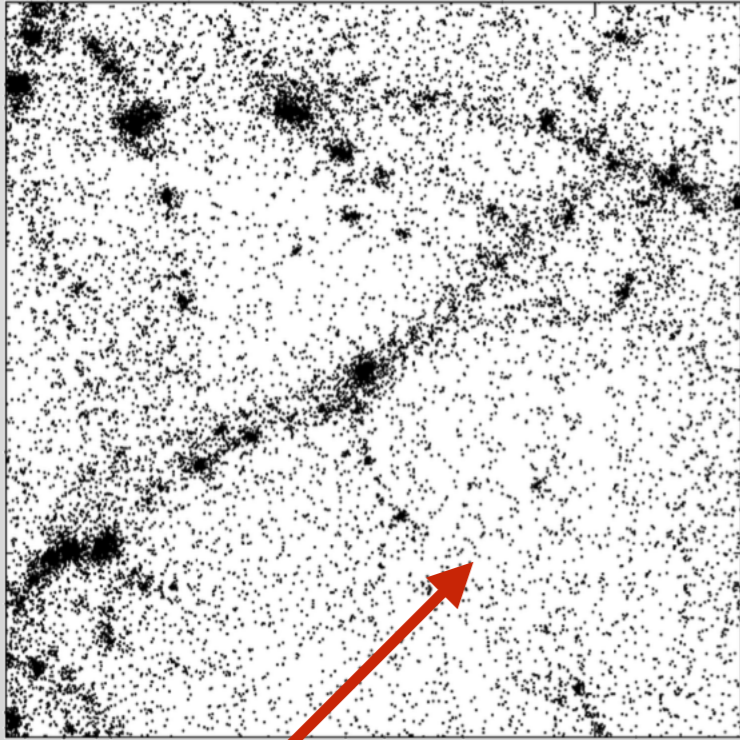


II

# Geometry and Local Density

(Ana Arcos)



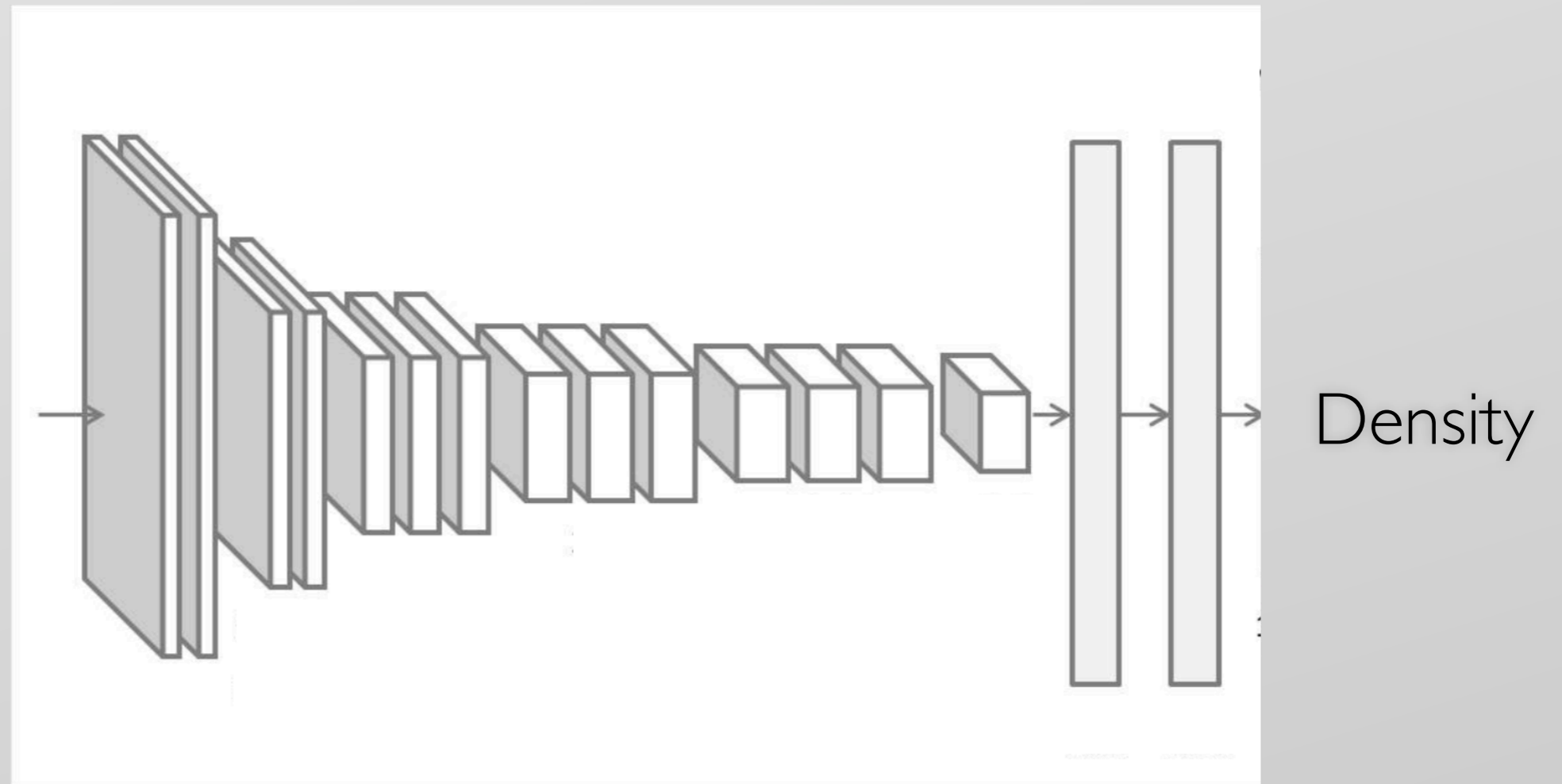
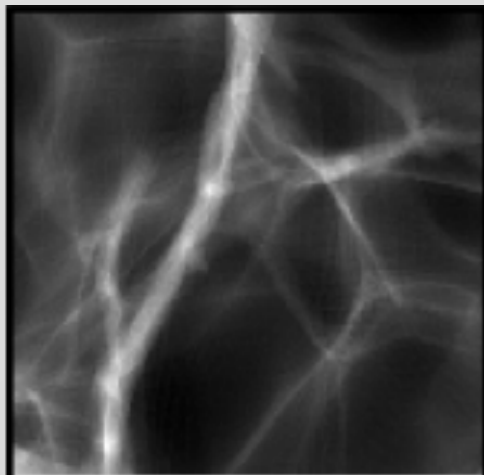


Hypothesis:

The complexity of the cosmic web is related to its local density.

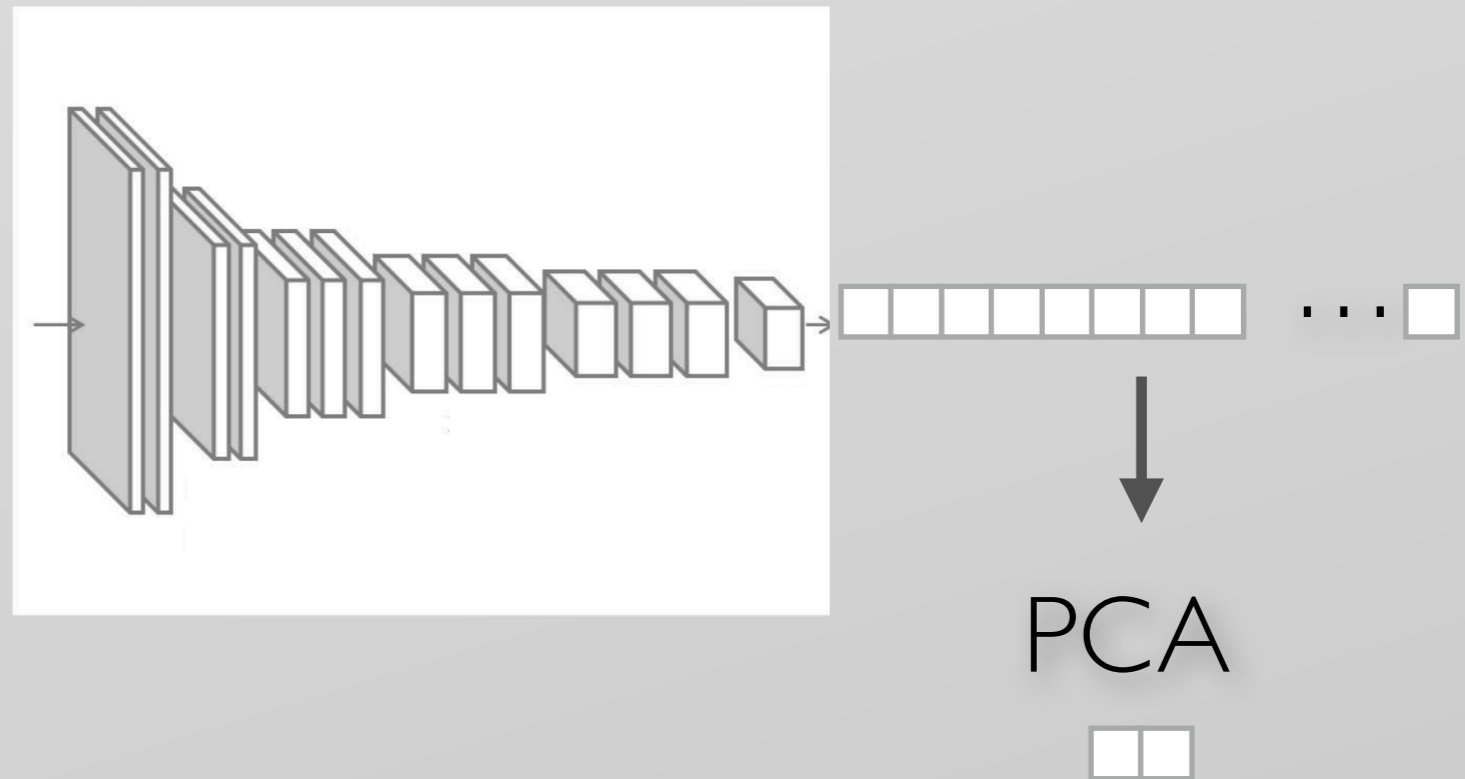
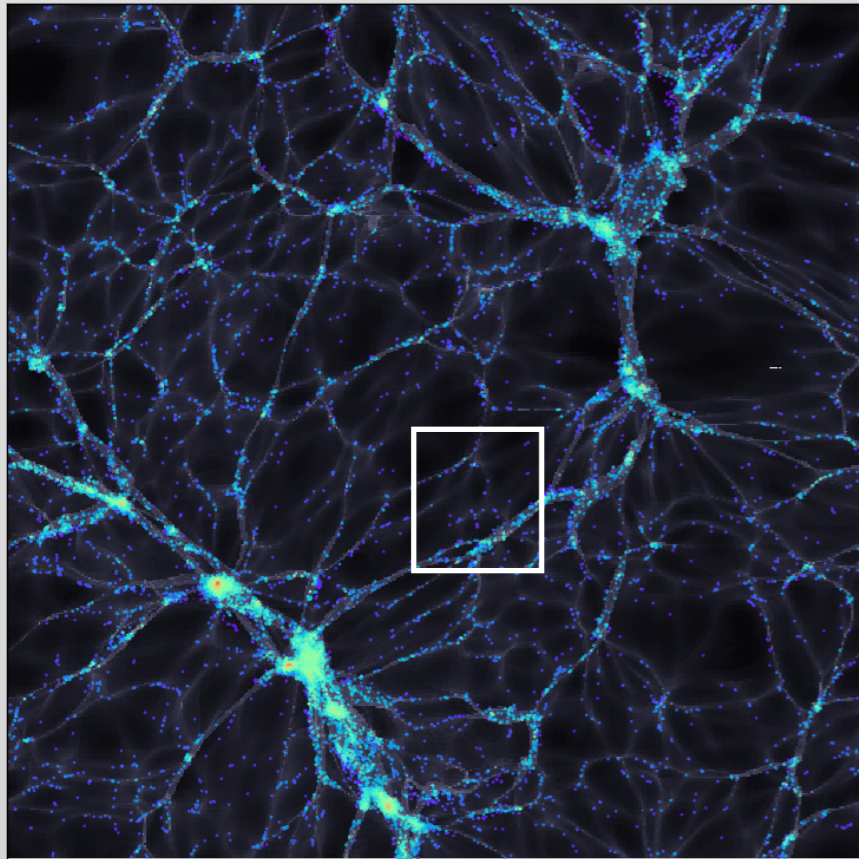
How can we quantify this ?

# Ask a Neural Network!

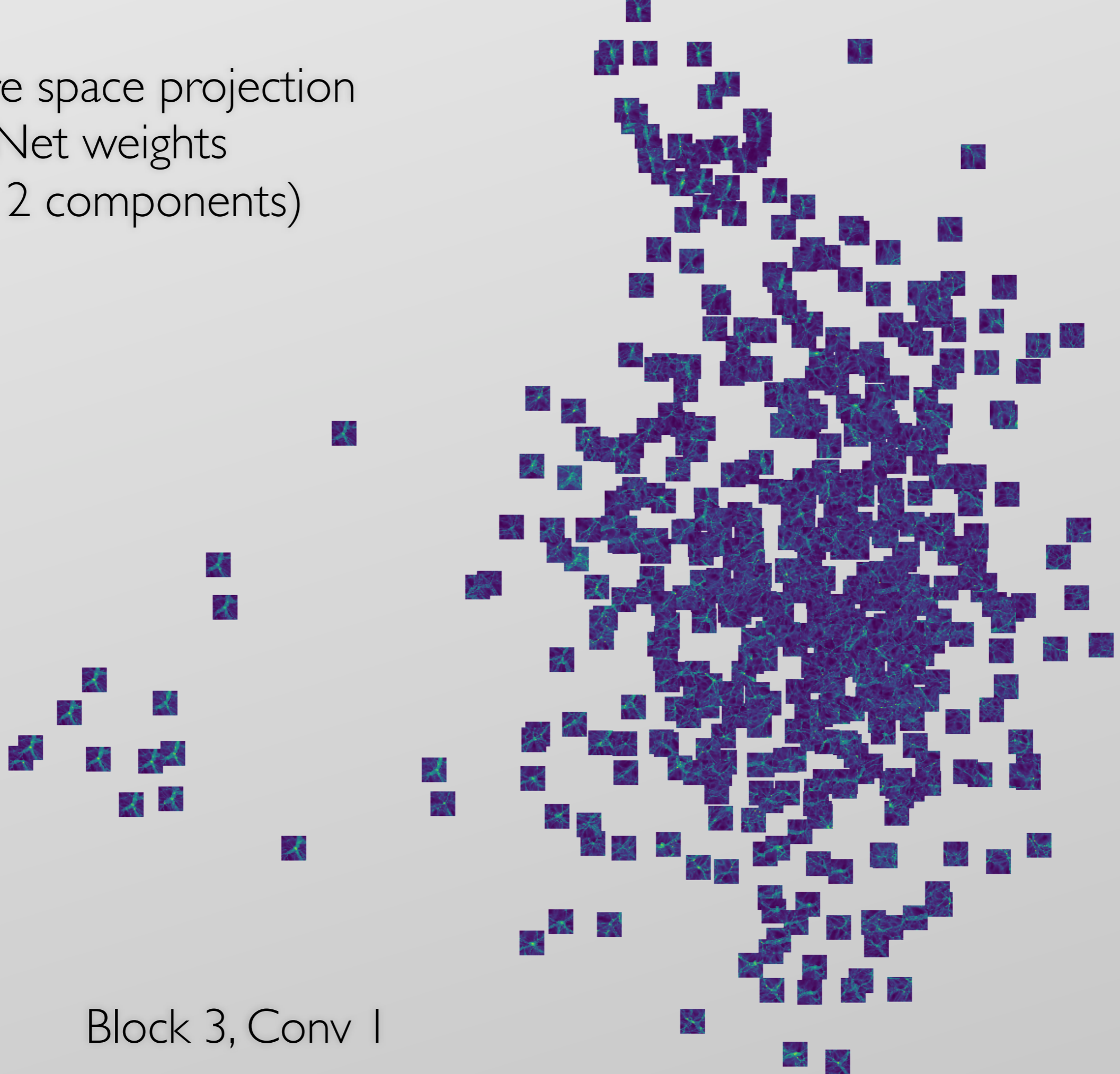


Assumption: if there is a pattern the neural net will find it

First some exploration with feature images ...

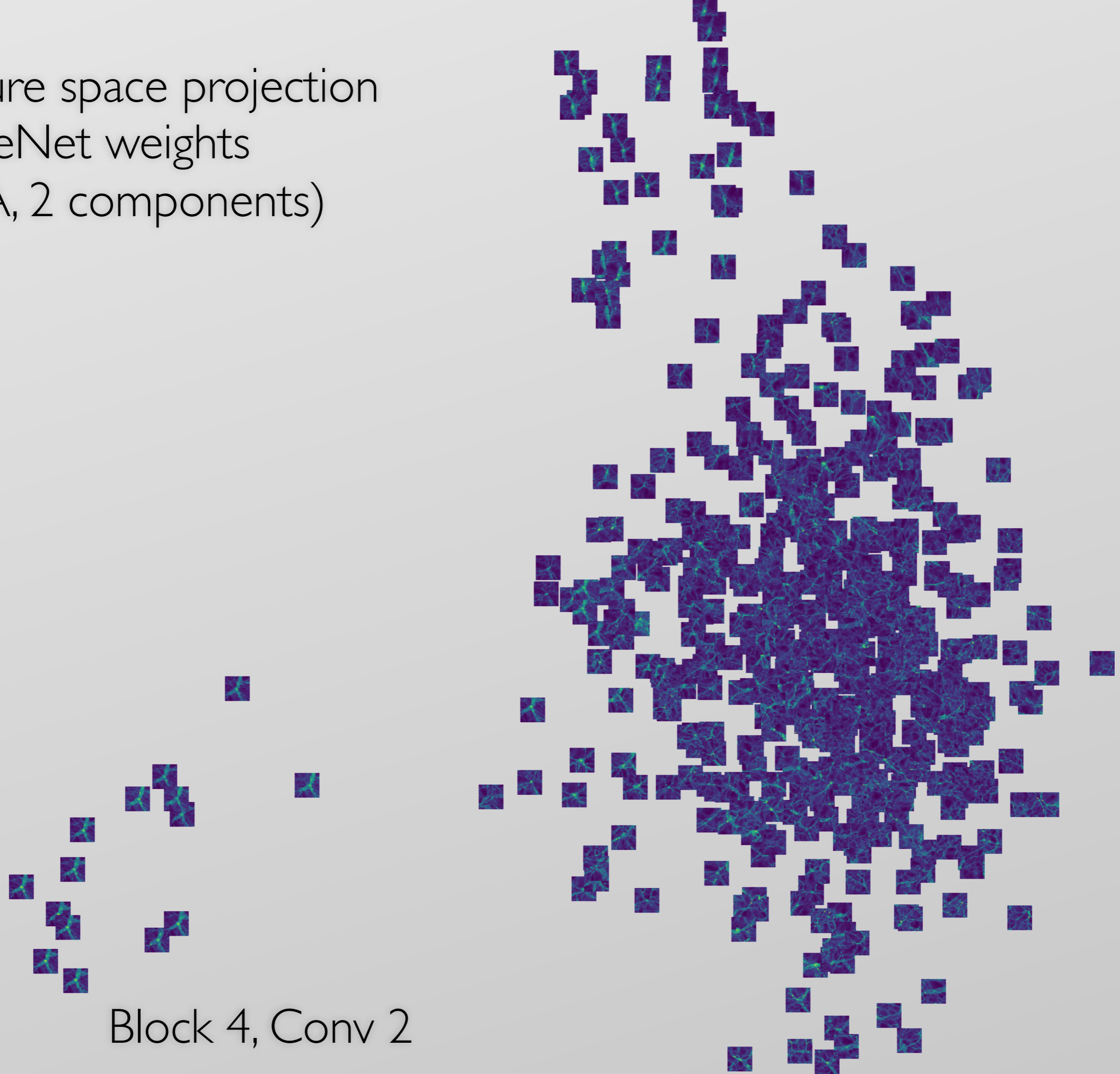


Feature space projection  
ImageNet weights  
(PCA, 2 components)



Block 3, Conv 1

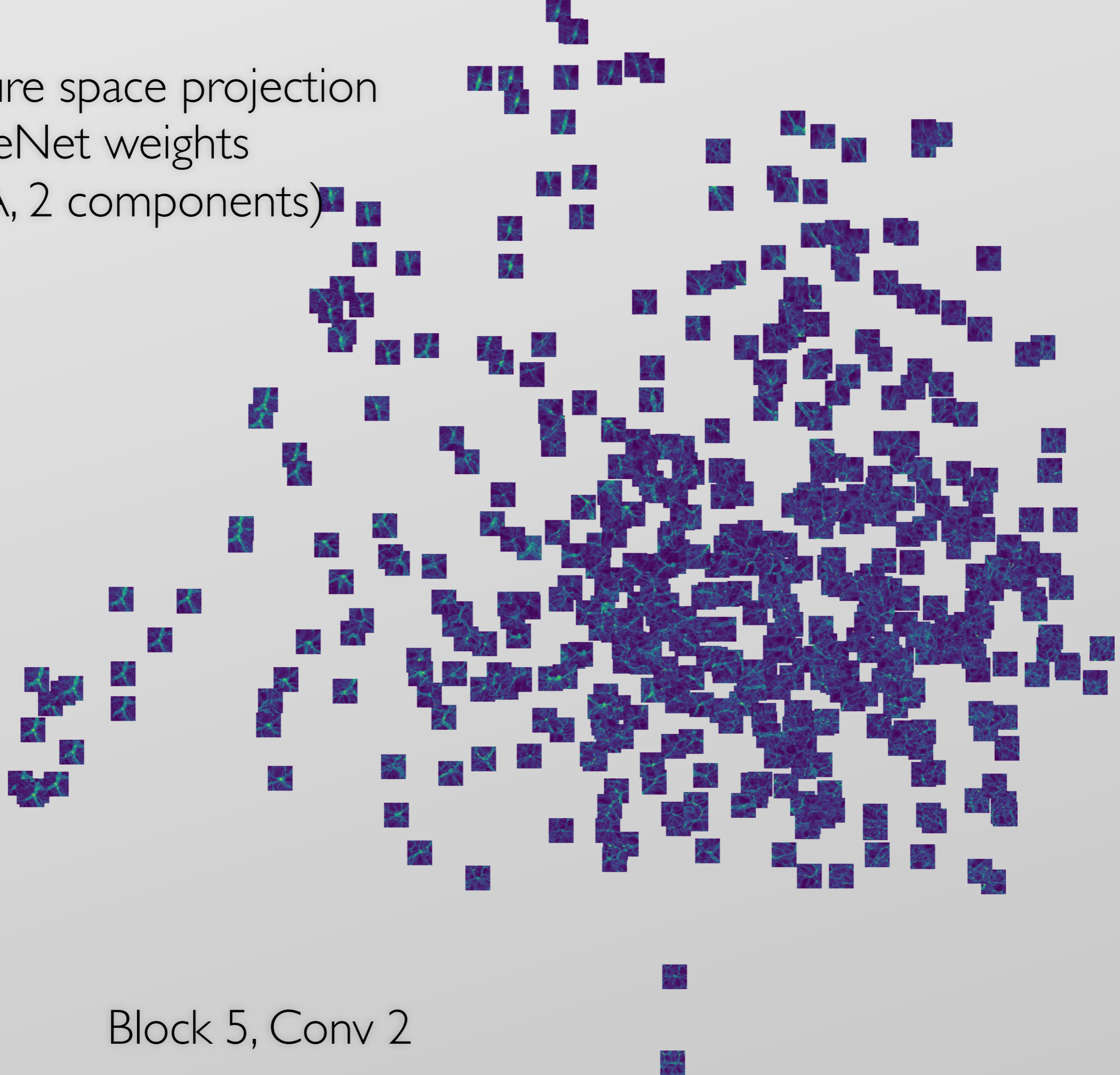
Feature space projection  
ImageNet weights  
(PCA, 2 components)



Block 4, Conv 2

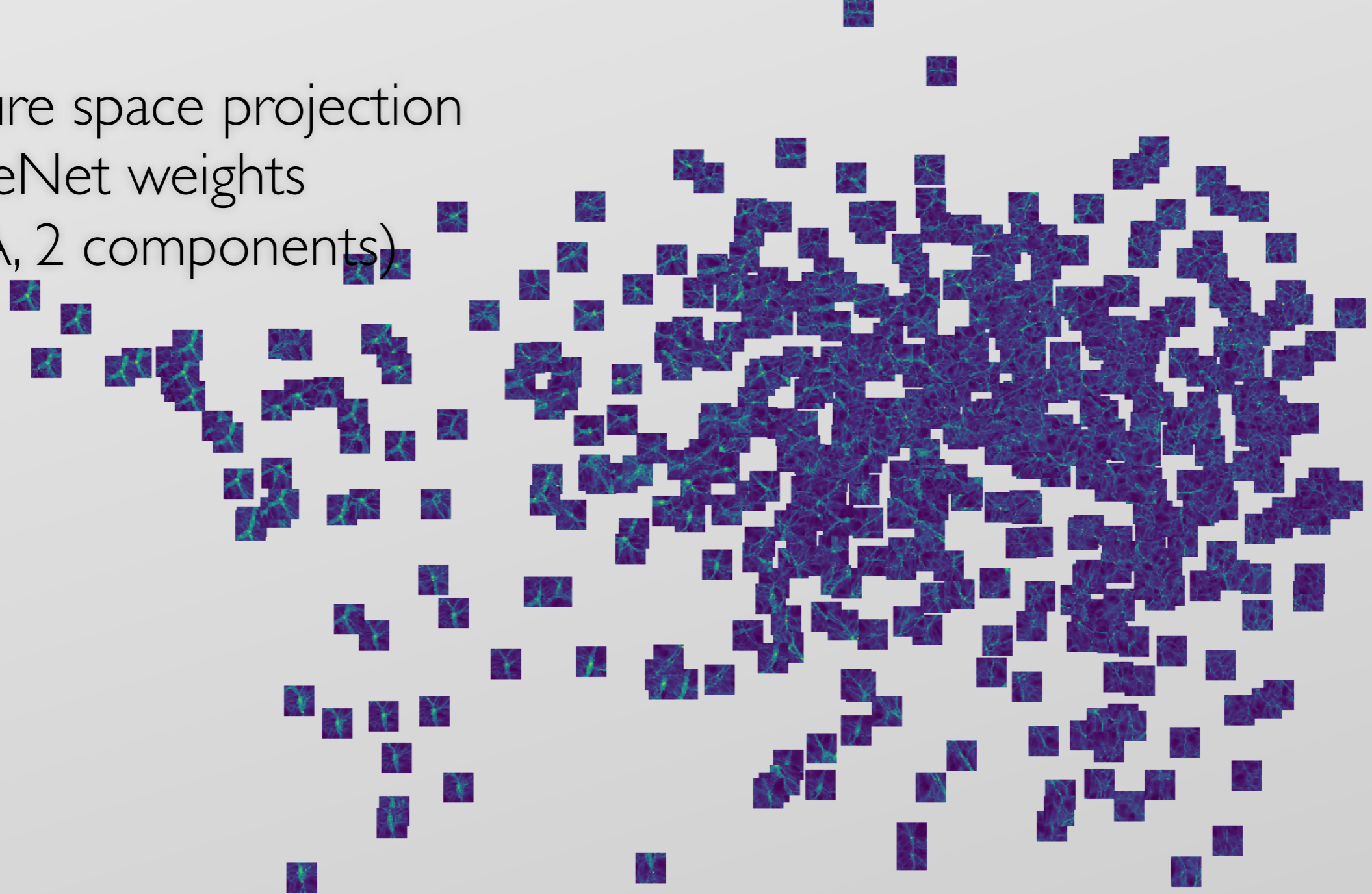


Feature space projection  
ImageNet weights  
(PCA, 2 components)



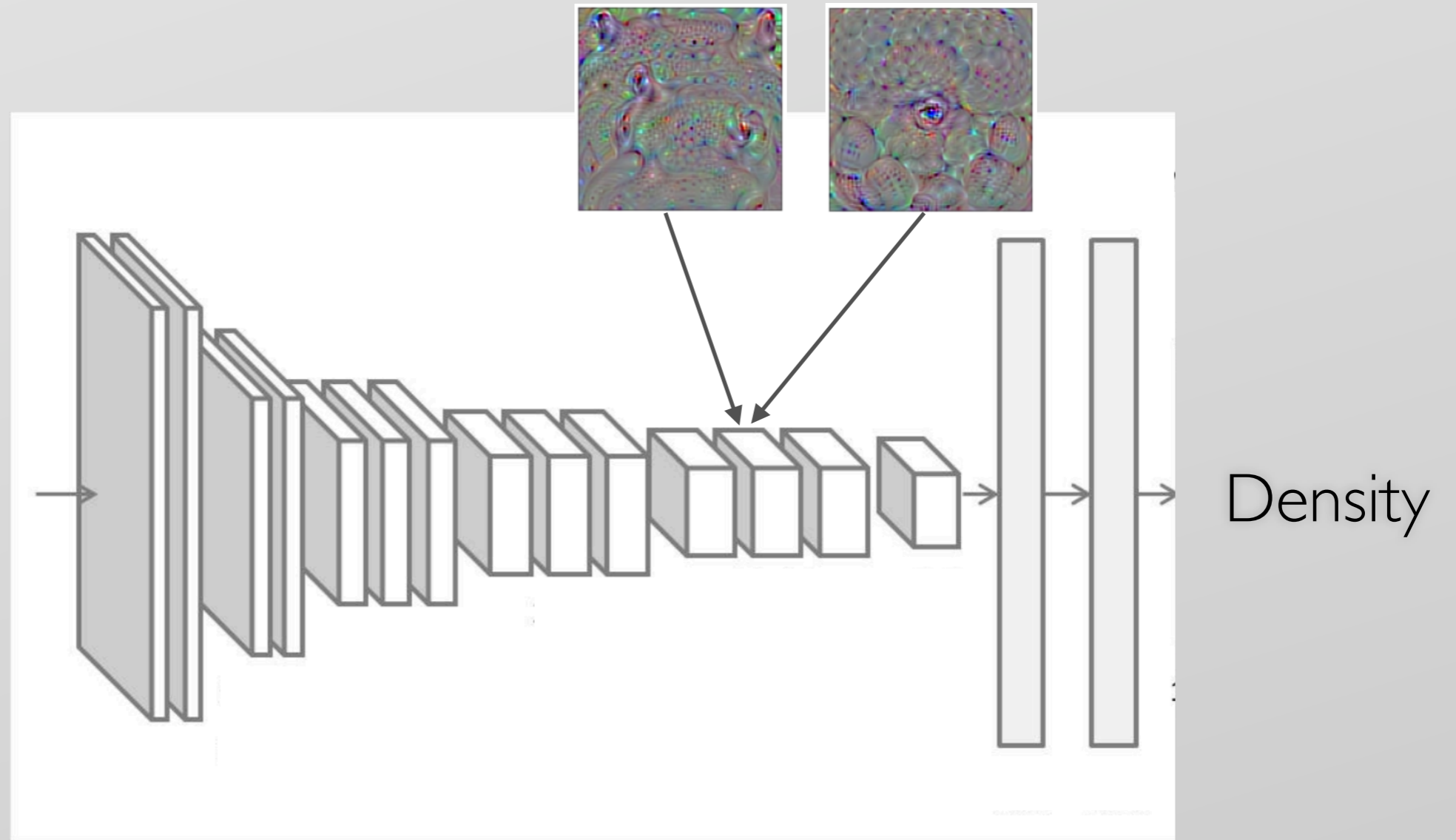
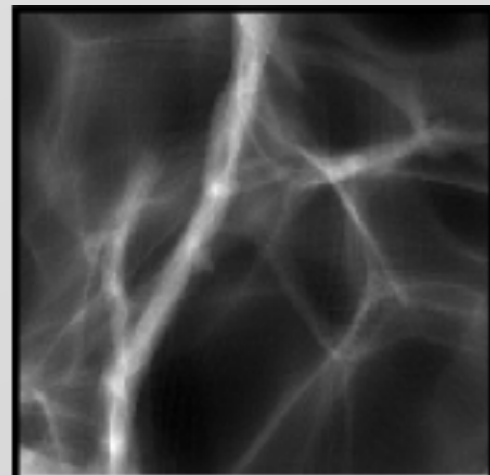
Block 5, Conv 2

Feature space projection  
ImageNet weights  
(PCA, 2 components)



Block 5, Conv 3

# Transfer Learning (VGG16 on ImageNet)



VGG16 (ImageNet)

Custom trainable

# Experiment setup

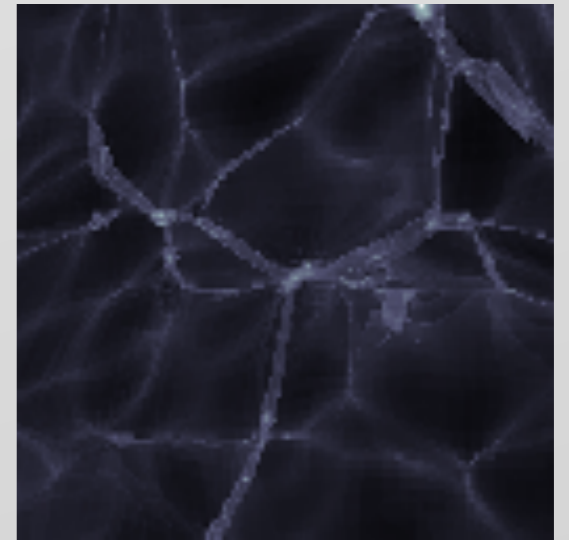
## Training data:

X: xy slice (18 Mpc side)

y: tophat density (2 Mpc)

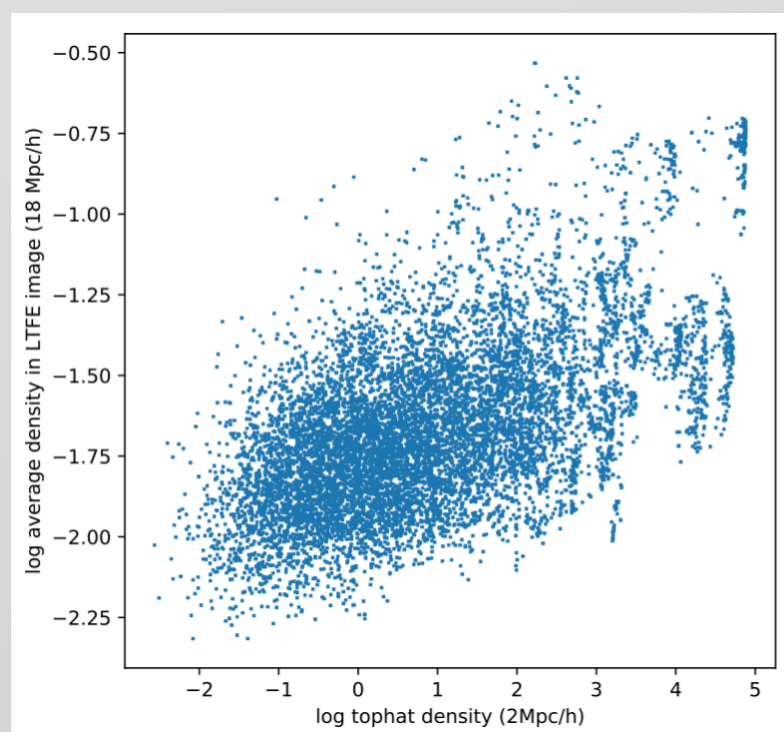
## Constraints:

Normalize values in range (0-1)

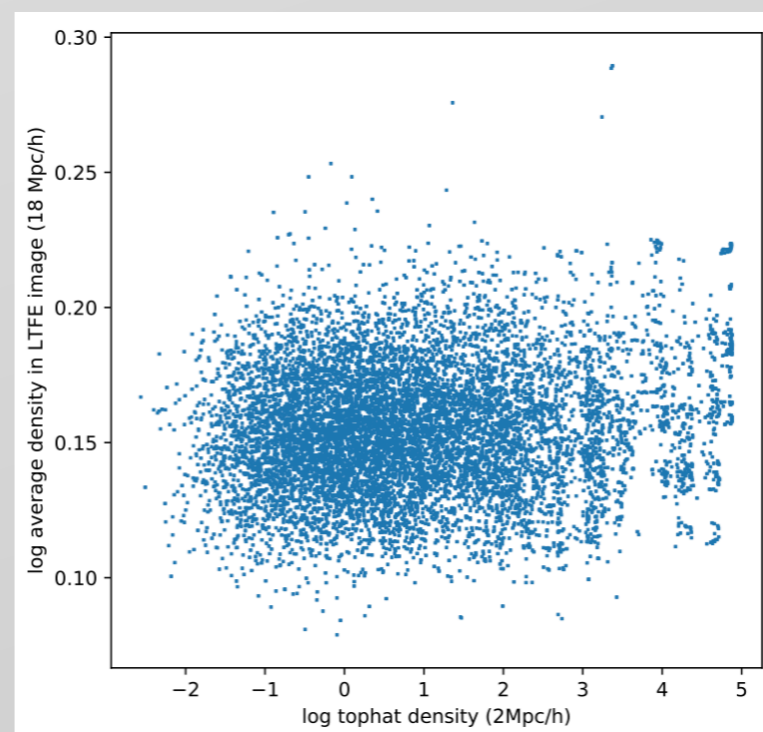


# Constraints:

Normalize values in range (0-1)



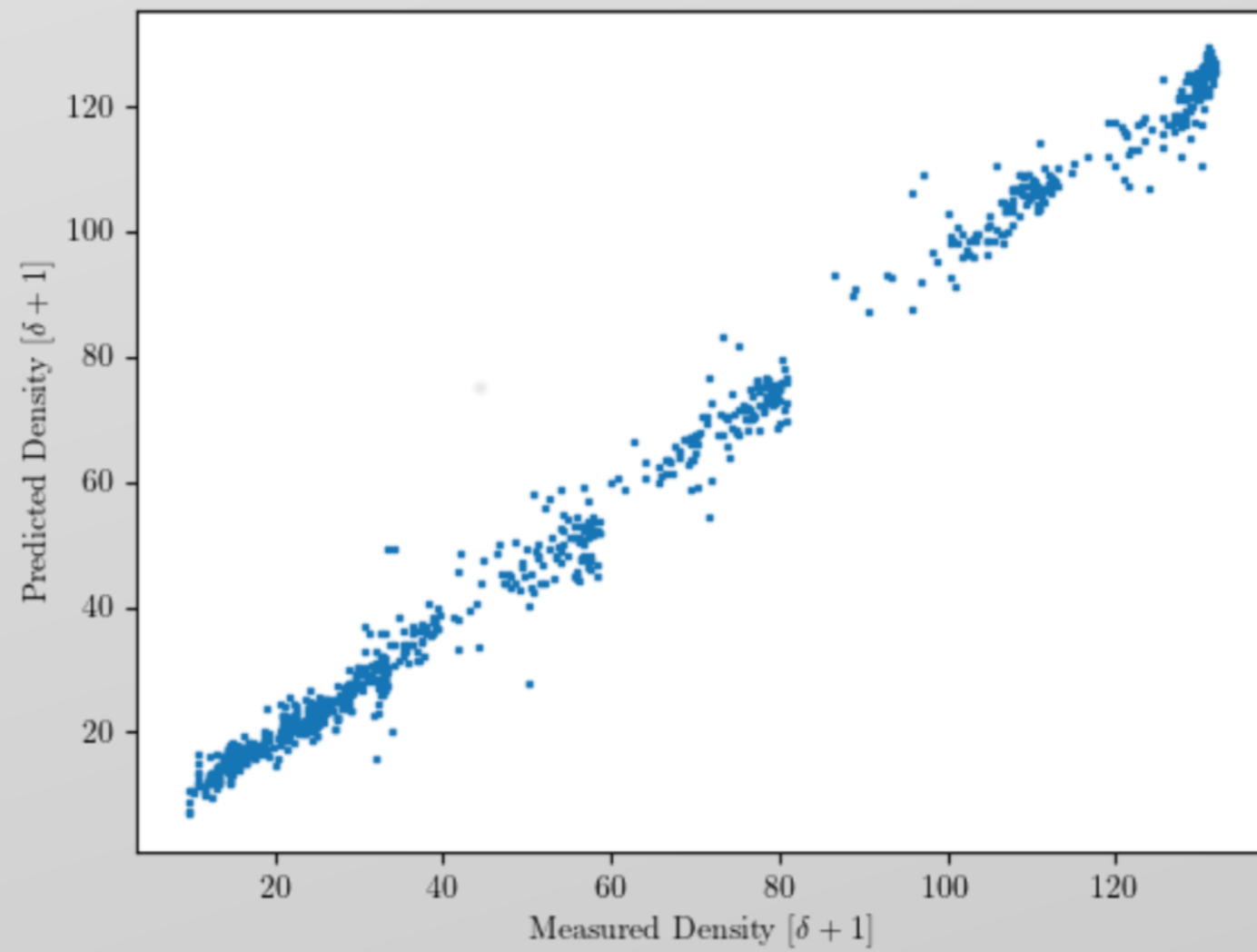
Original



Normalized

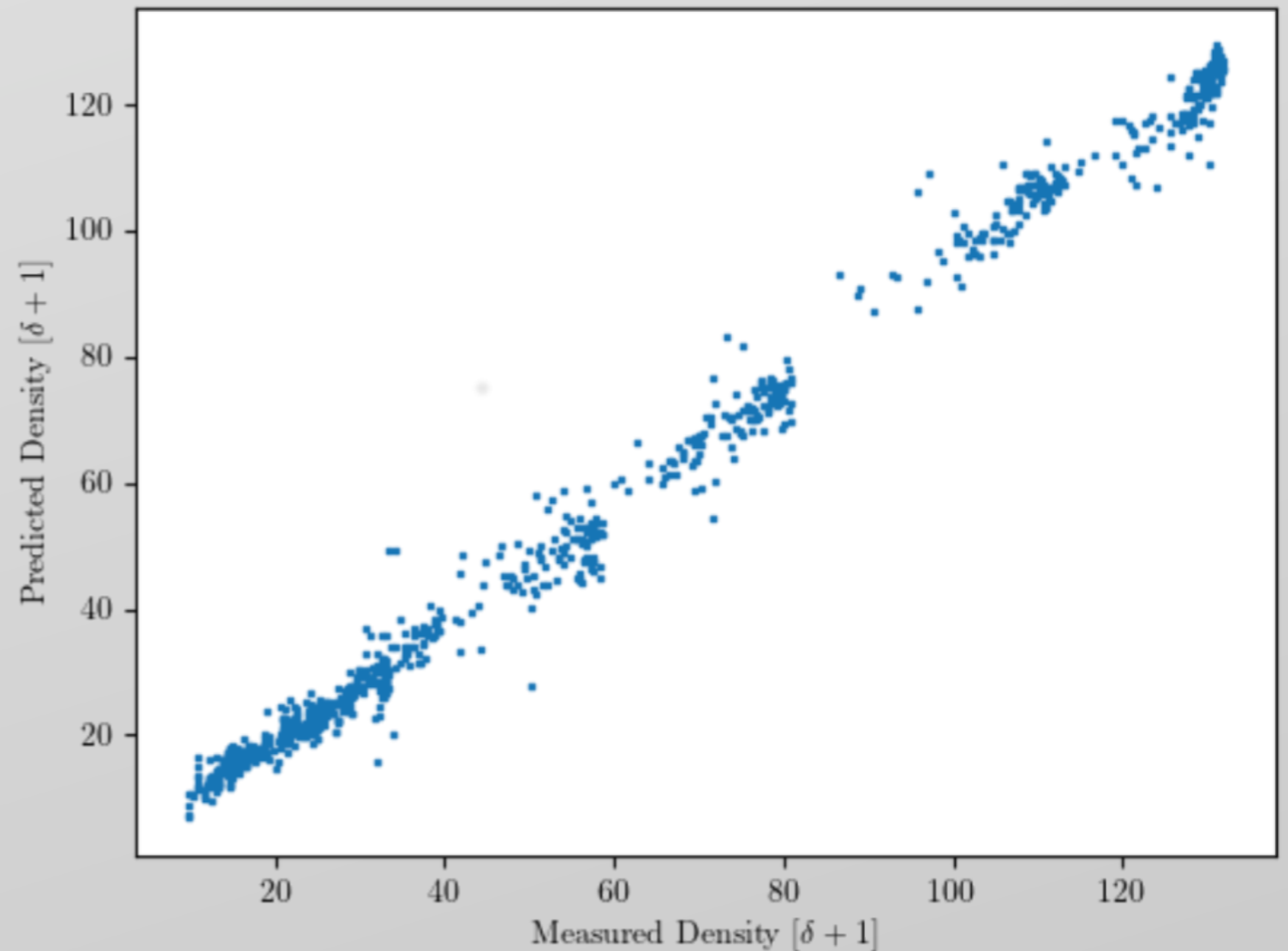
# Results

- VGG16 on ImageNet



To do (Ana):

- Use 3D net
- Train from scratch
- Test halo/galaxy properties
- etc.



III

# Image-z

(Martin Herrera)



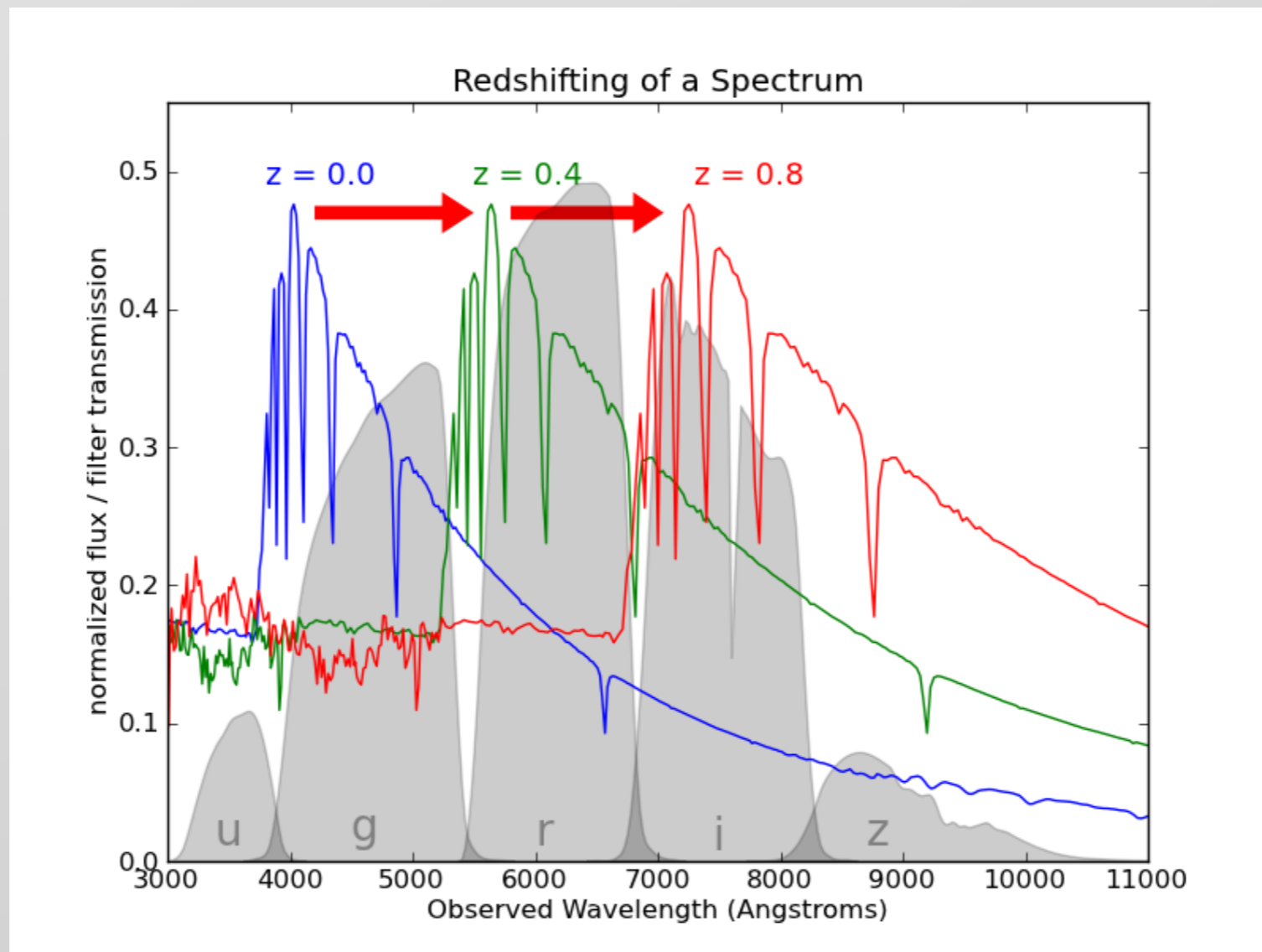


photo-z

Measuring photometric redshifts using galaxy images  
and Deep Neural Networks

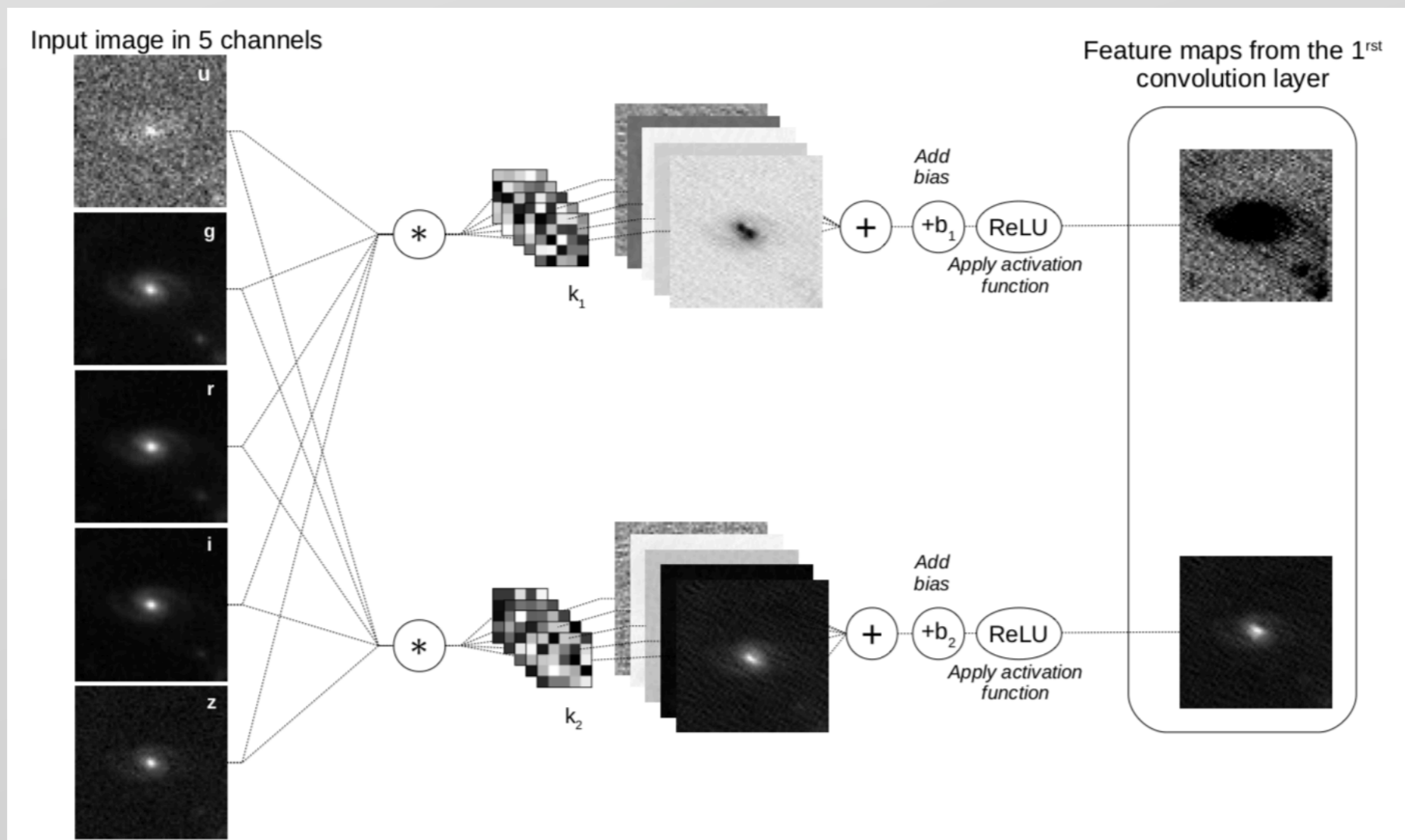
Ben Hoyle

**Photometric redshifts from SDSS images using a Convolutional  
Neural Network**

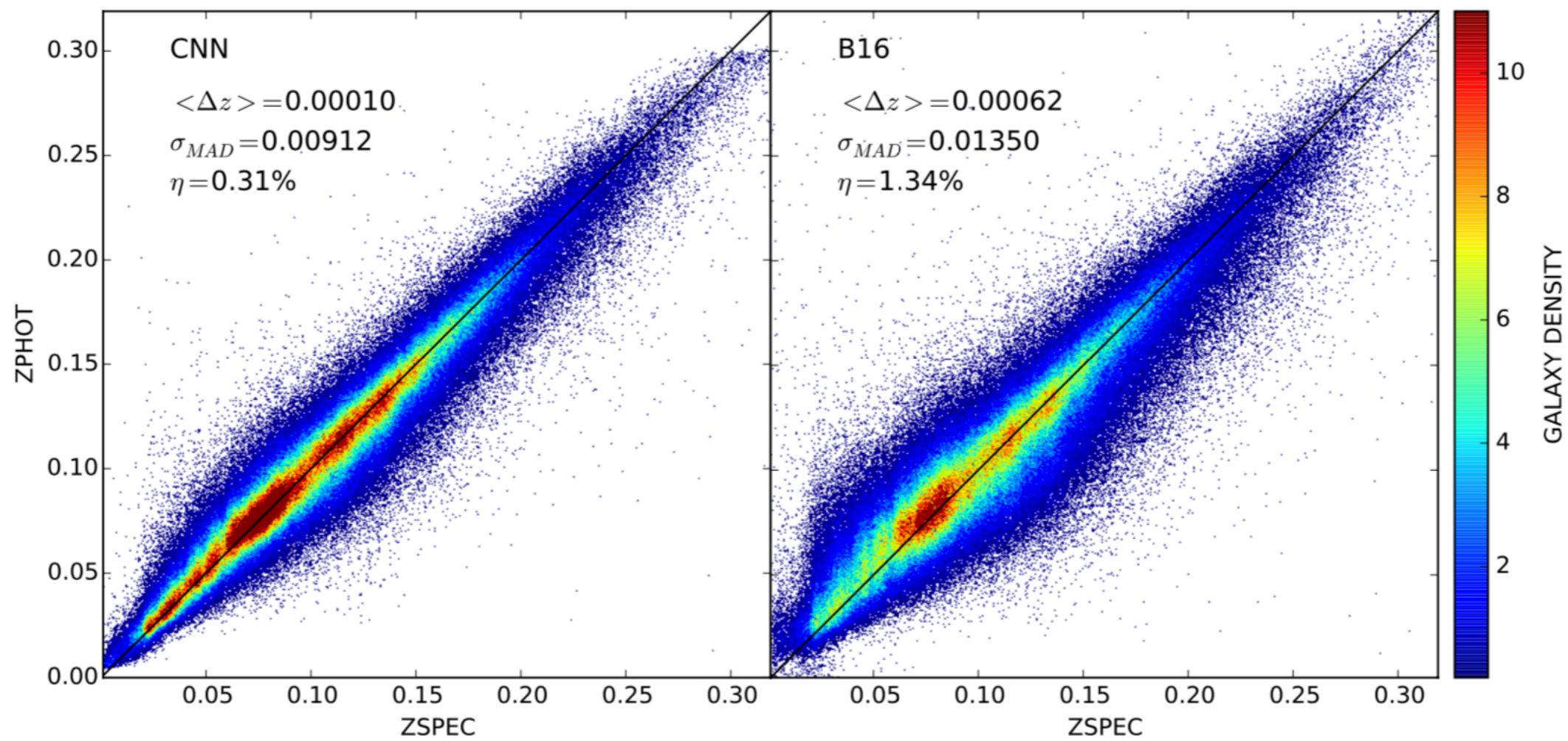
Johanna Pasquet<sup>1</sup>, E. Bertin<sup>2</sup>, M. Treyer<sup>3</sup>, S. Arnouts<sup>3</sup> and D. Fouchez<sup>1</sup>

**Photometric redshift estimation via deep learning**  
**Generalized and pre-classification-less, image based, fully probabilistic redshifts**

A. D'Isanto and K. L. Polsterer



Pasquet et al. 2018



**Fig. 7.** Comparison between the photometric redshifts predicted by the CNN (left panel) and by B16 (right panel) against the spectroscopic redshifts. The galaxy density and the statistics are averaged over the 5 cross-validation samples.

Pasquet et al. 2018

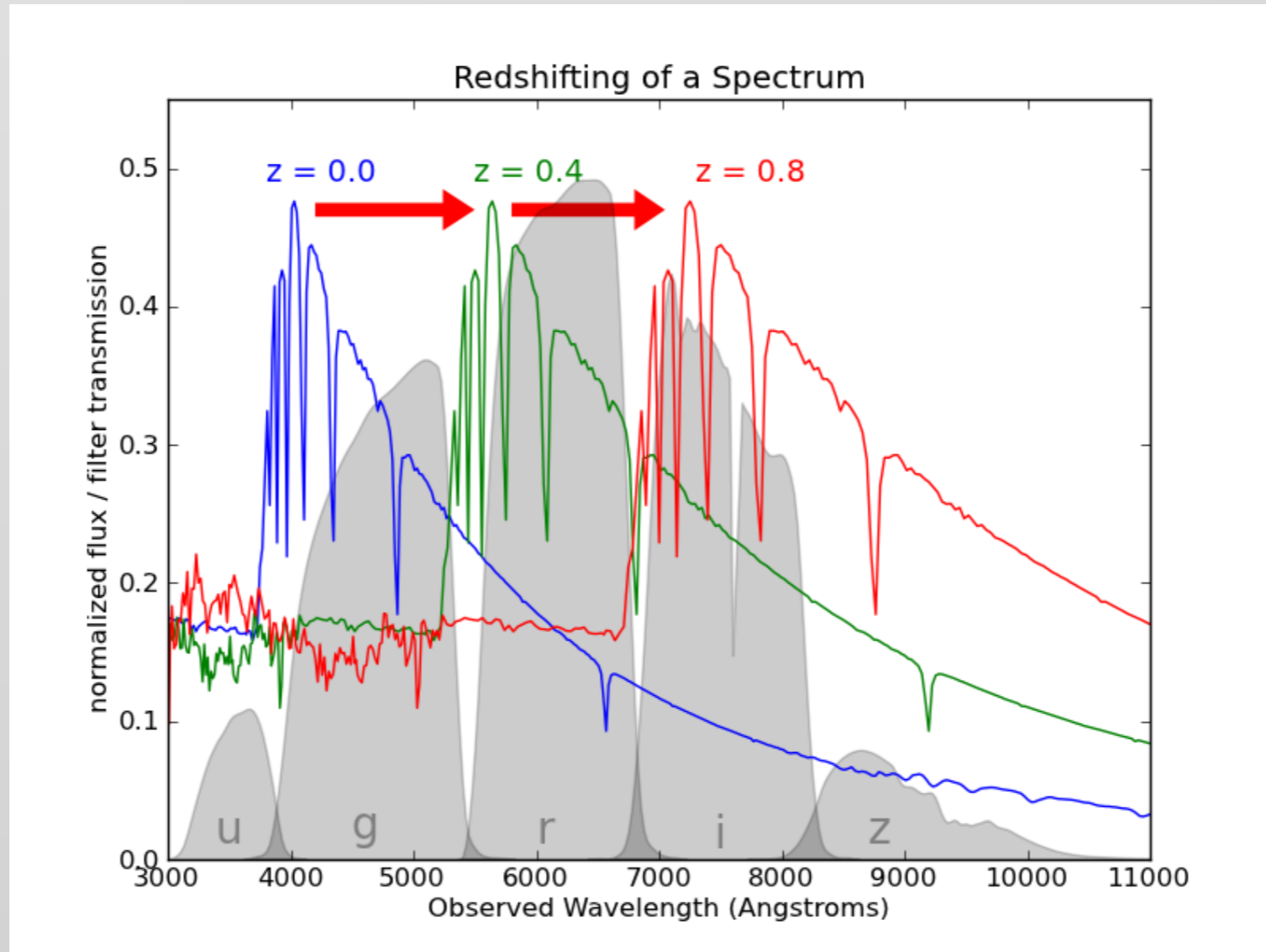
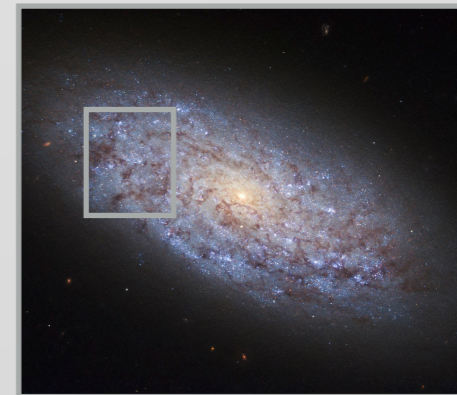


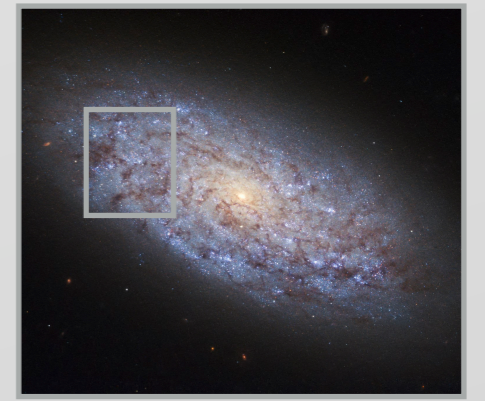
photo-z

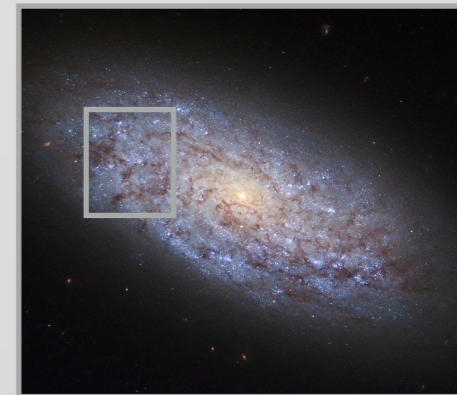


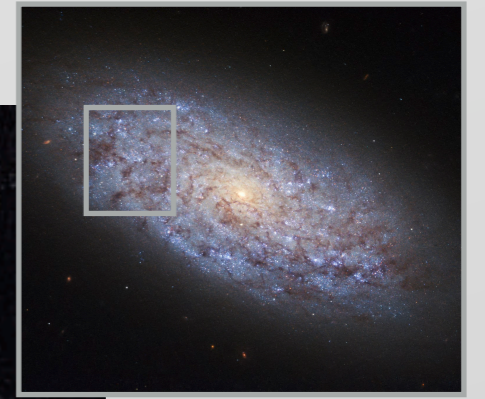


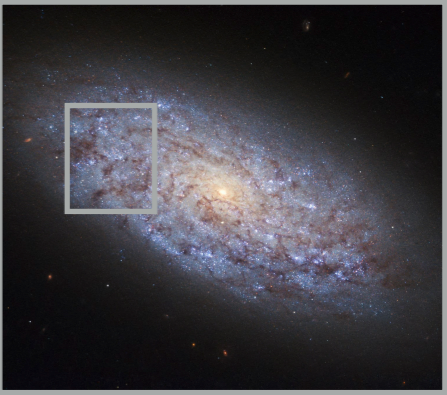














NGC 5949 (~5 kpc radius)



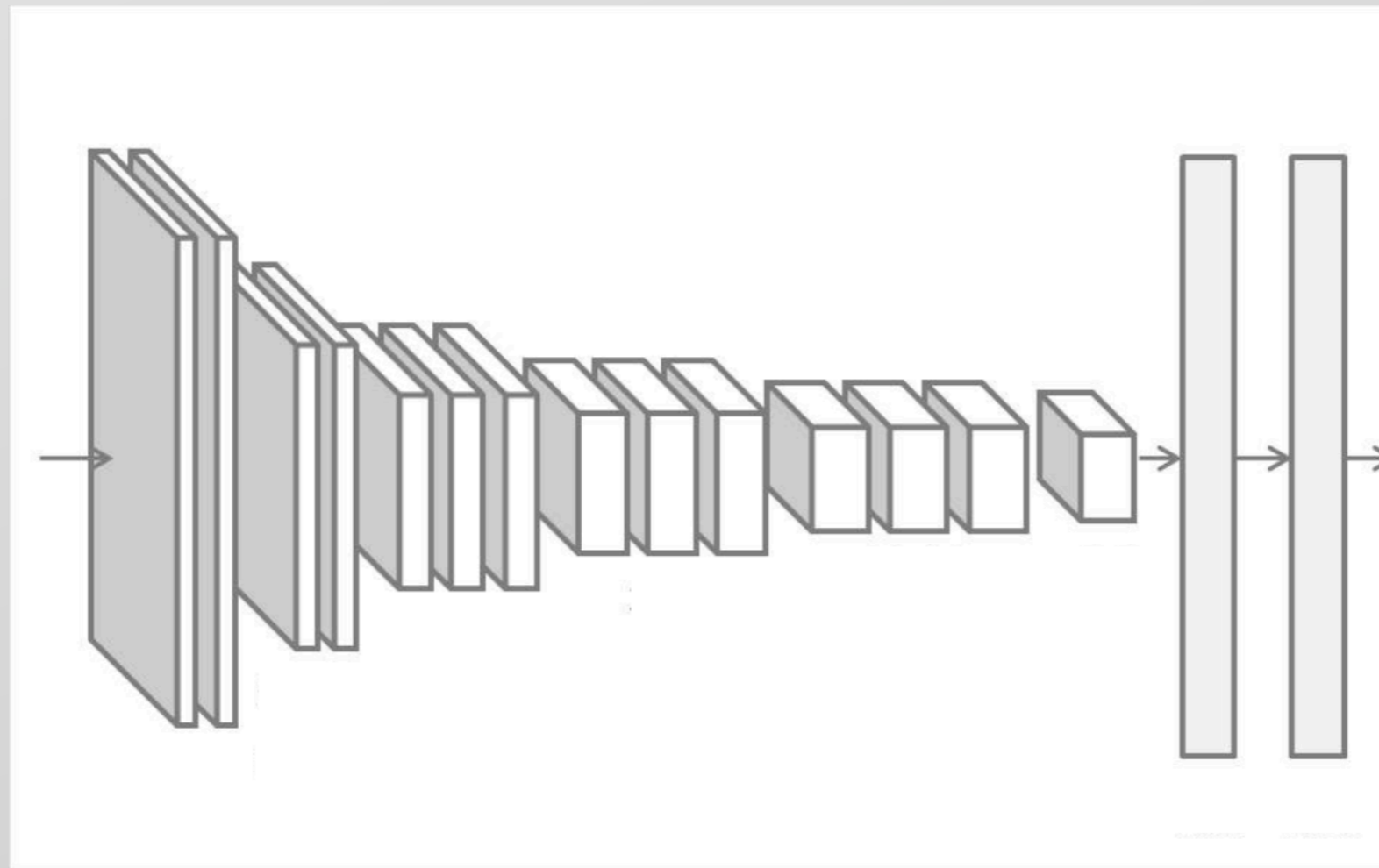
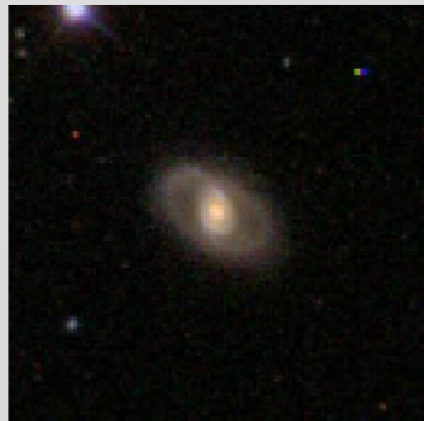
NGC 5457 (~30 kpc radius)

Hypothesis:

There are structural elements in galaxies with constrained physical scales. We can use these elements as standard rulers.

How can we quantify the structure in galaxies ?

Use a neural network !!!

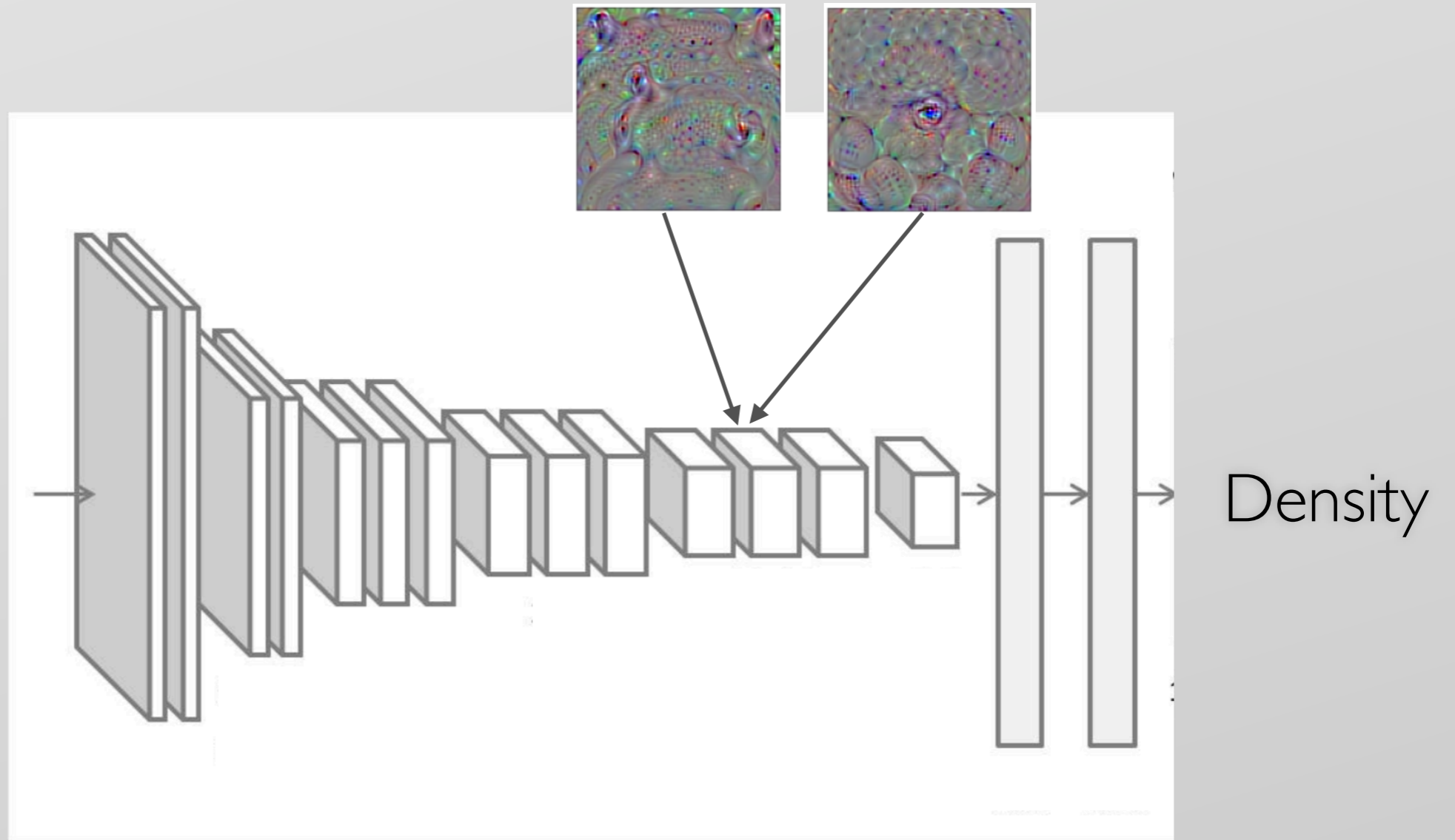
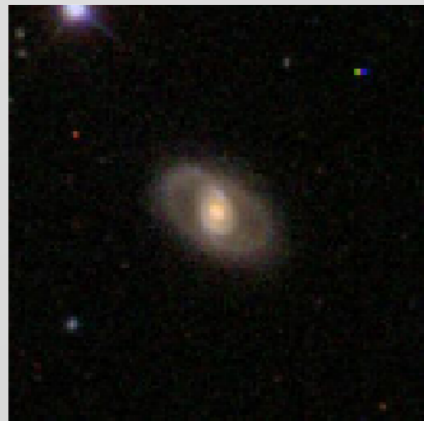


VGG16 (ImageNet)

Custom  
trainable

Density

# Transfer Learning (VGG16 on ImageNet)

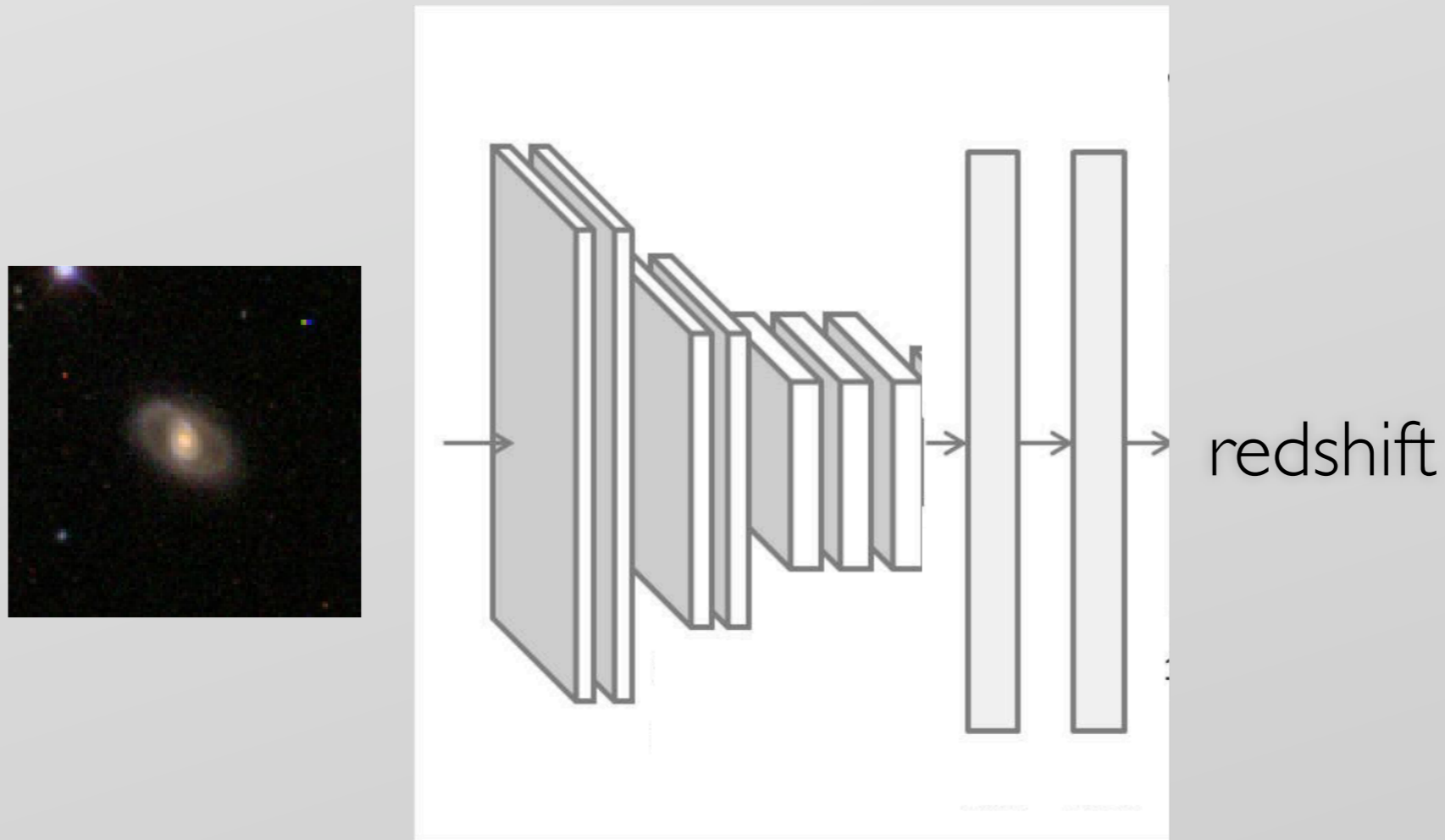


VGG16 (ImageNet)

Custom trainable



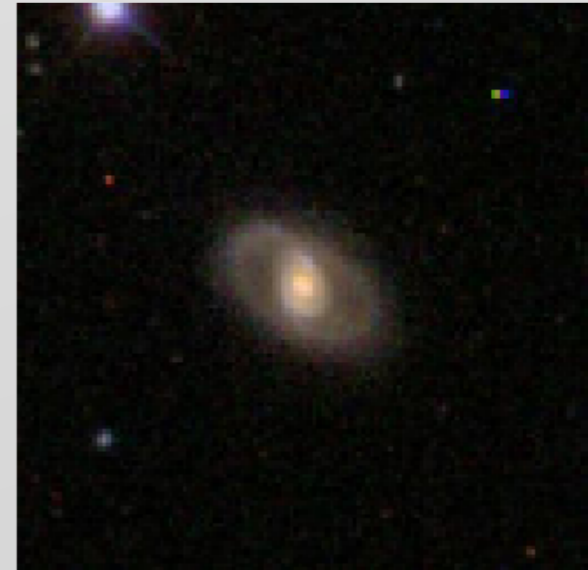
# Transfer Learning (VGG16 on ImageNet)



VGG16 (ImageNet)

Custom  
trainable

# Experiment setup



## Training data:

X: single channel image

y: redshift

## Constraints:

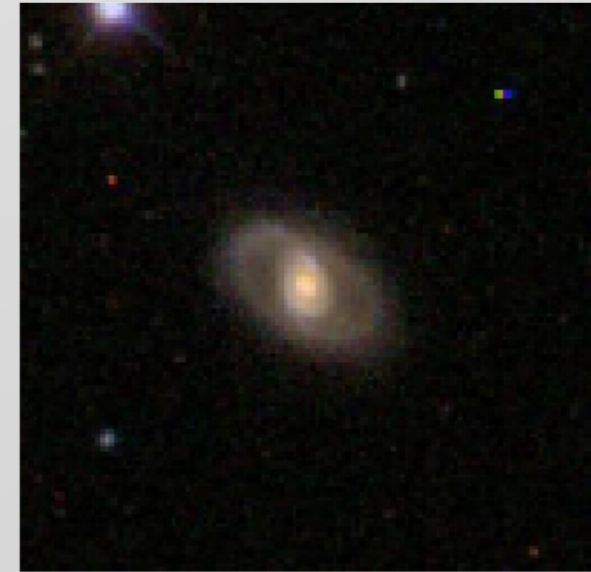
Large images

Spirals (galaxy zoo class)

Face-on ( $b/a > 0.75$ )

Same angular size

# Experiment setup



## Training data:

X: single channel image

y: redshift

## Constraints:

Large images

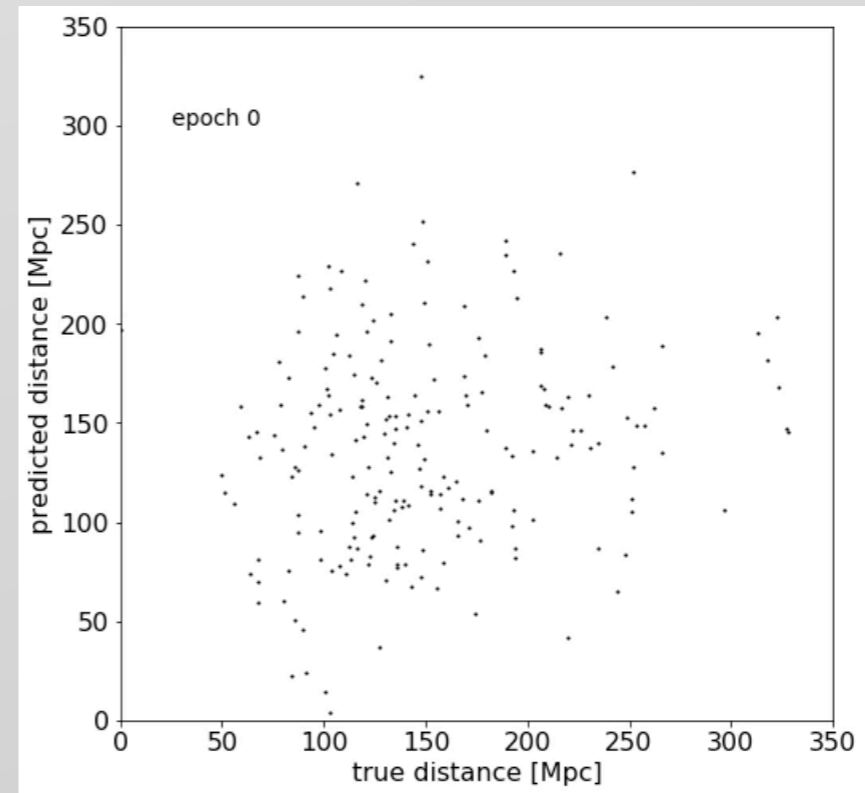
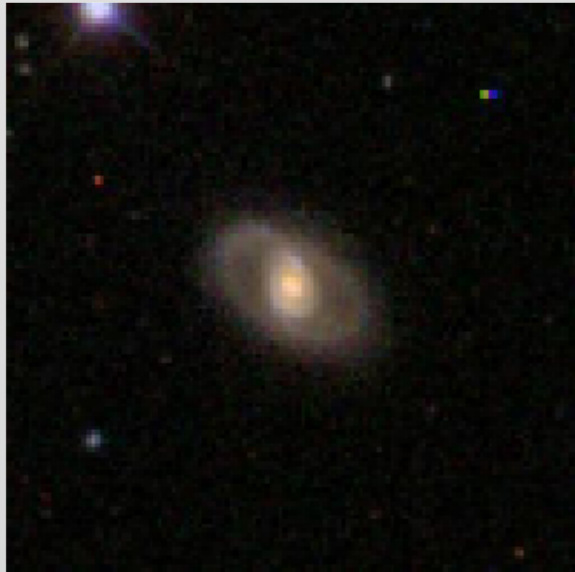
Spirals (galaxy zoo class)

Face-on ( $b/a > 0.75$ )

Same angular size

JPG images (!)

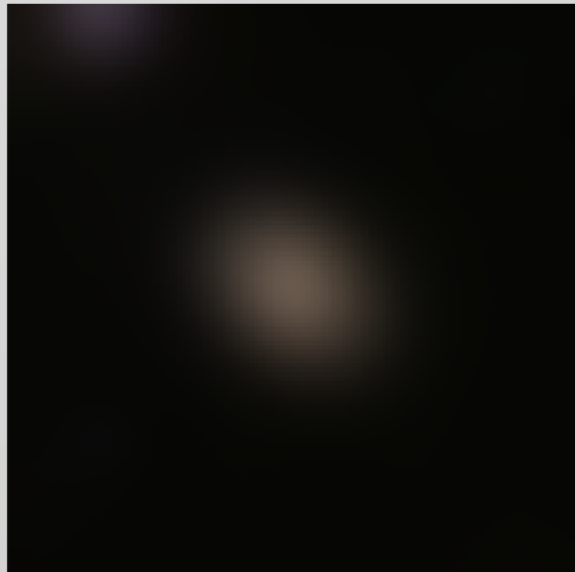
# Results (raw images)



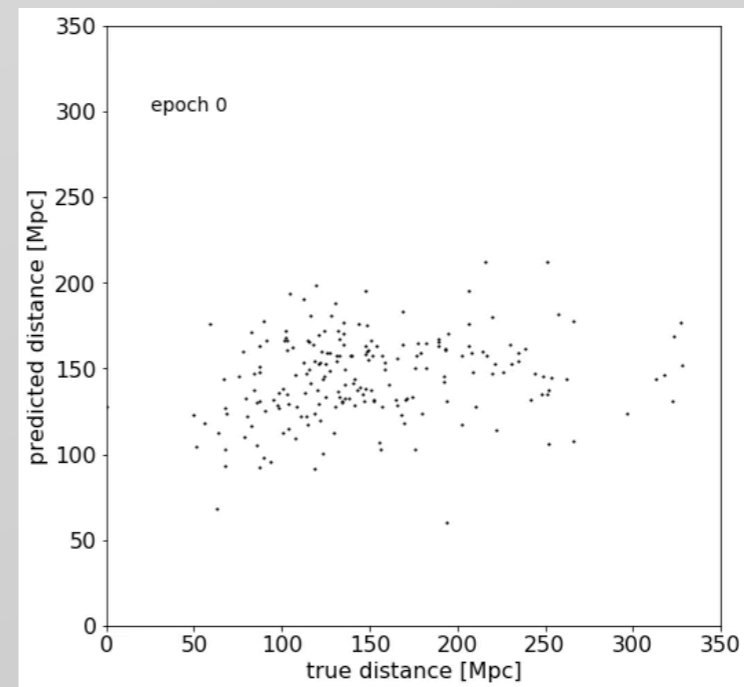
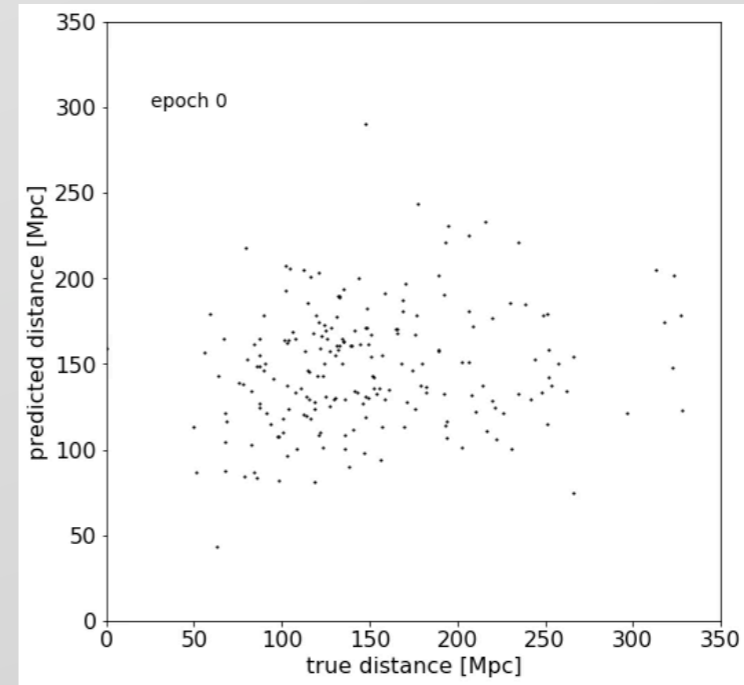
# Results (smoothing)



4 pix



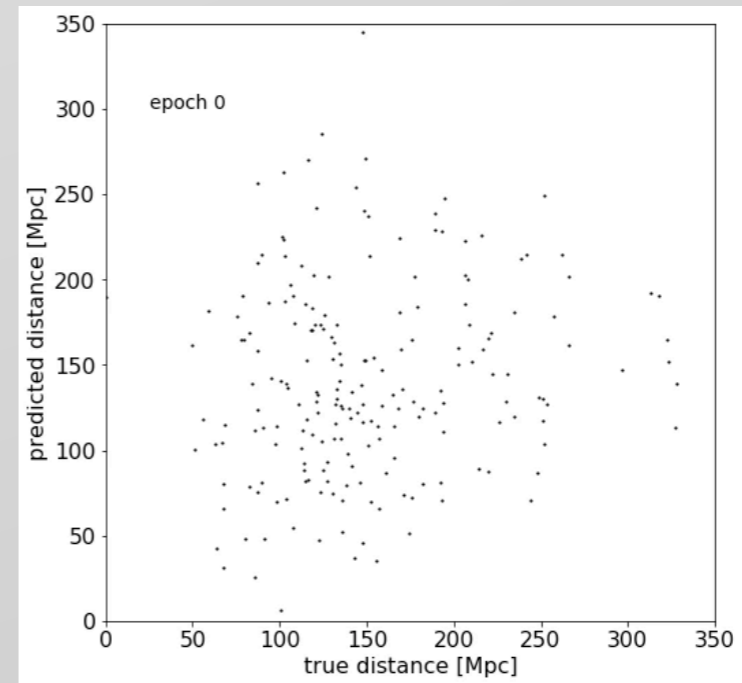
8 pix



# Results (high-pass)



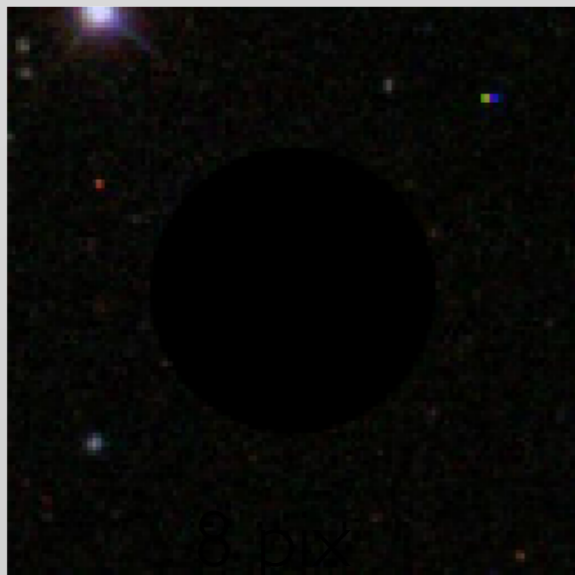
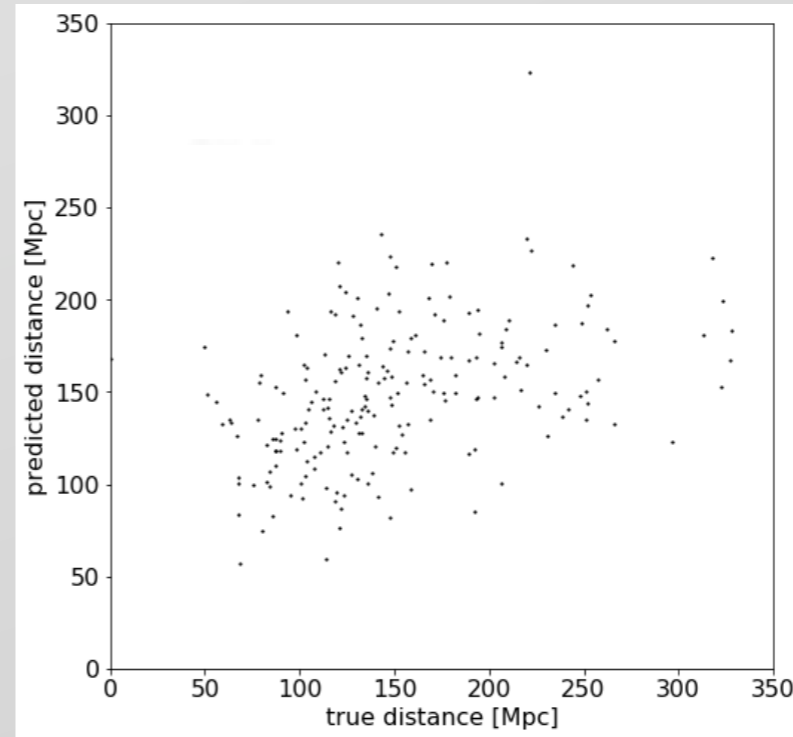
8 pix



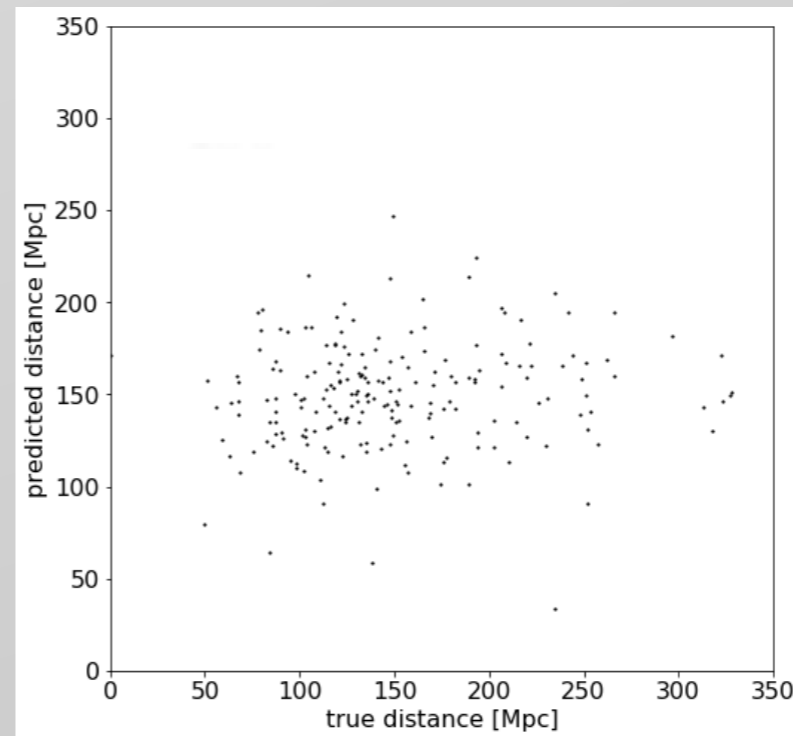
# Results (foreground / background)



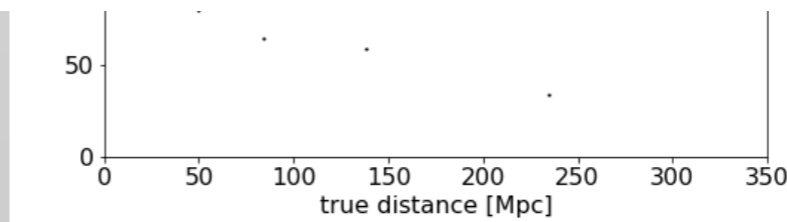
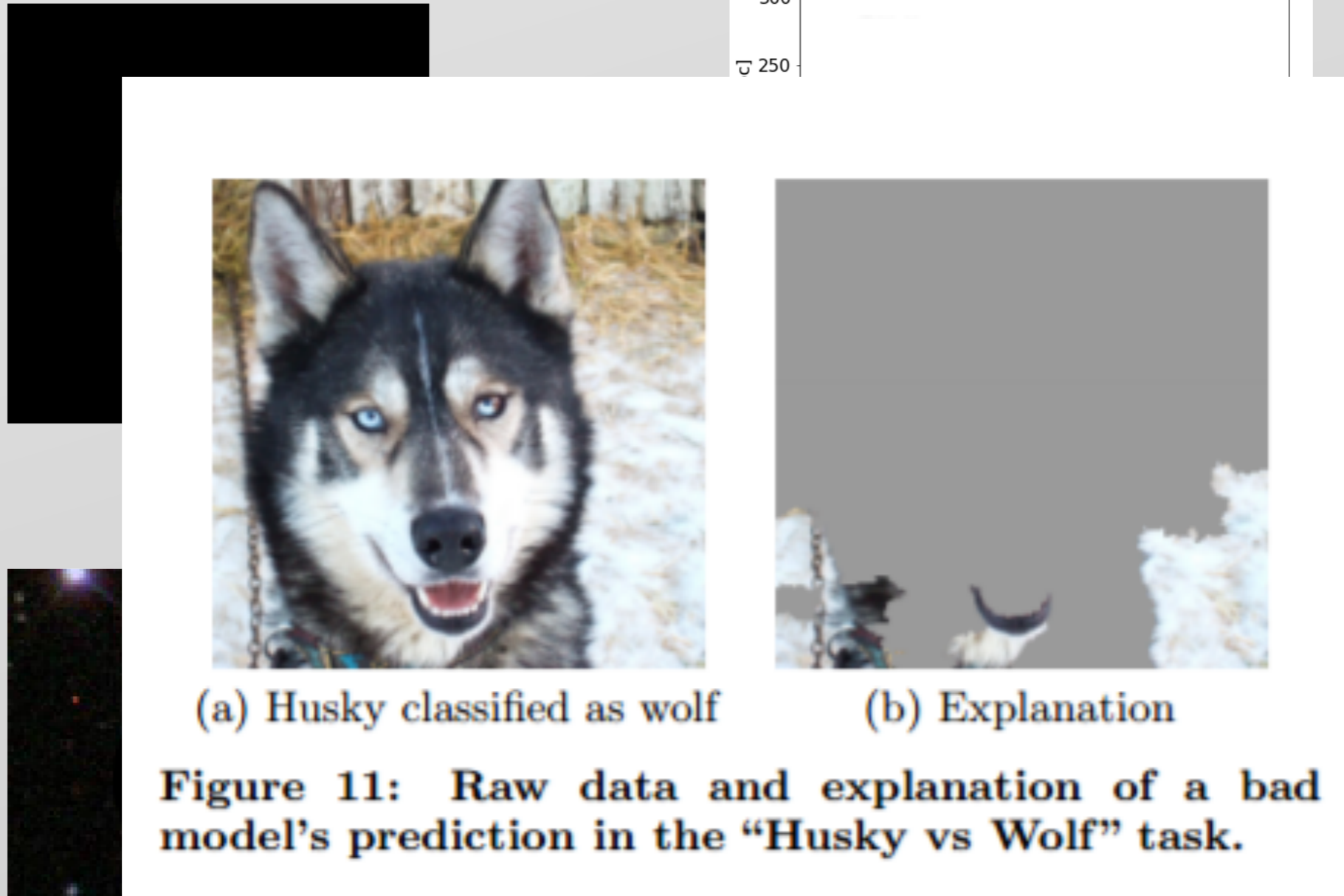
Center



Outskirts



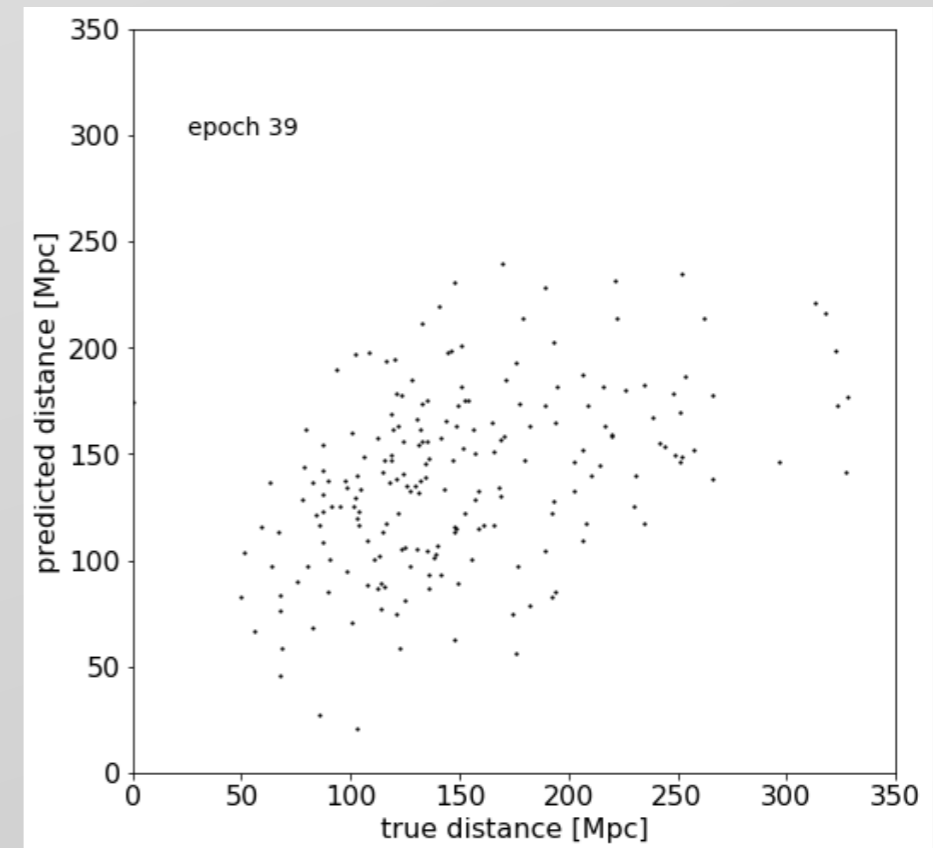
# Results (foreground / background)





## To do (Martin)

- Use fits images
- Multiscale analysis
- Explore features
- Add to existing photo-z methods





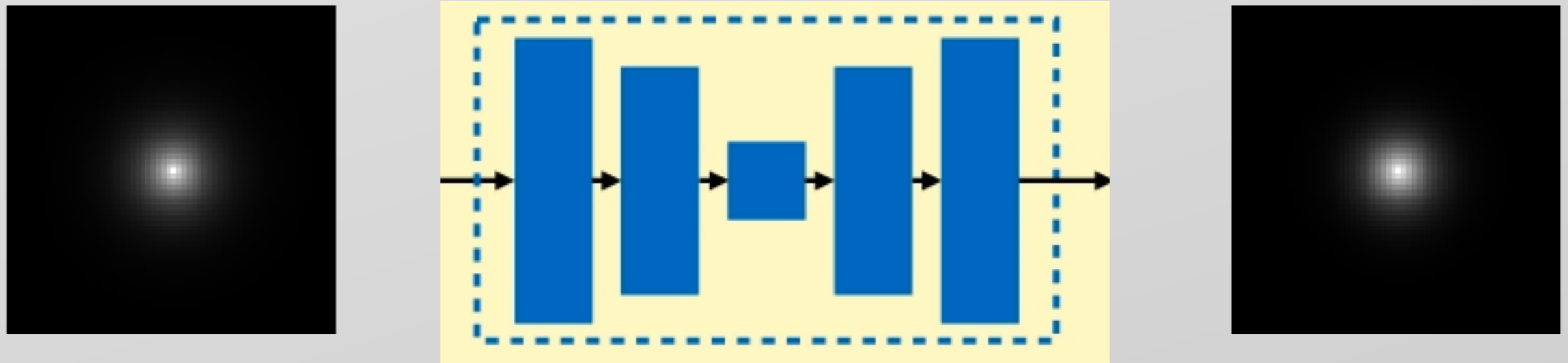
# Conclusions

Artificial Intelligence is a black box (so far) but can be used as a powerful hypothesis testing tool

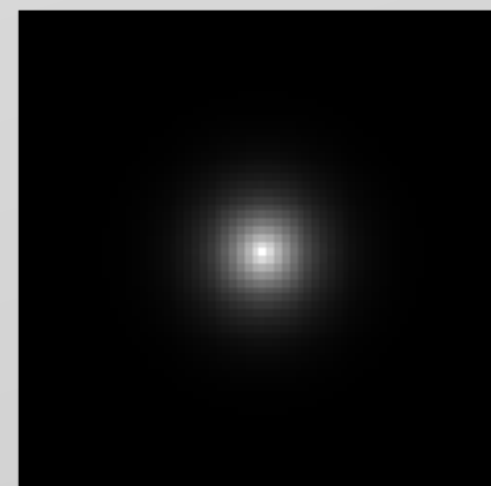
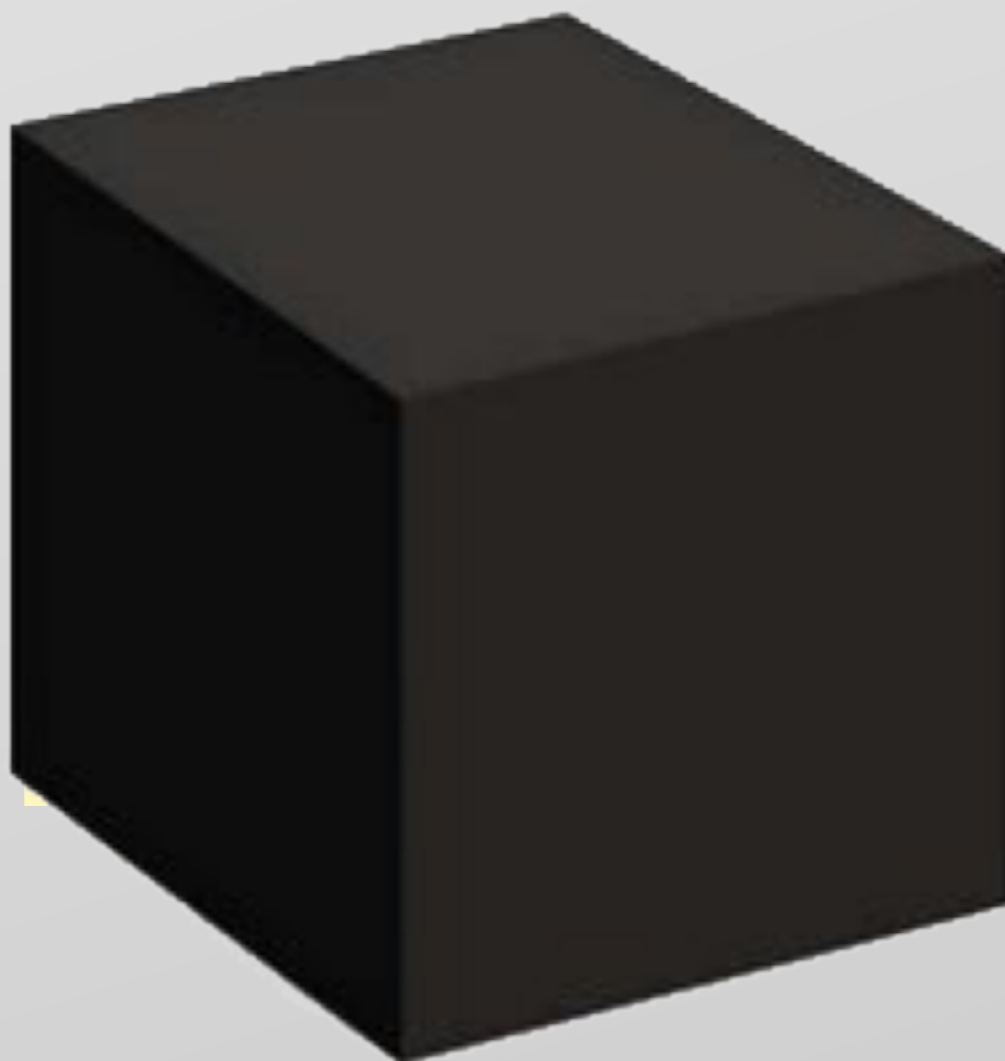
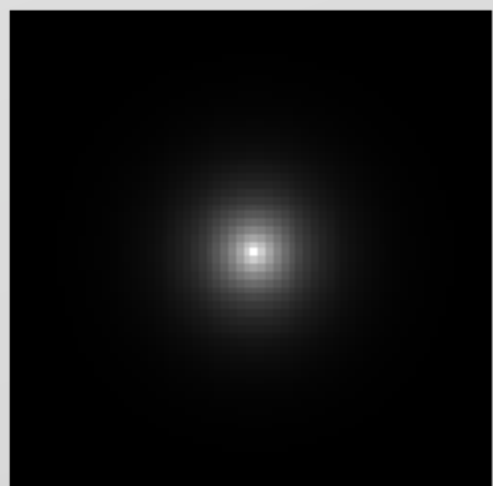
With some constraints on the training process we can also extract insight on the data

Thank you!

# Autoencoder

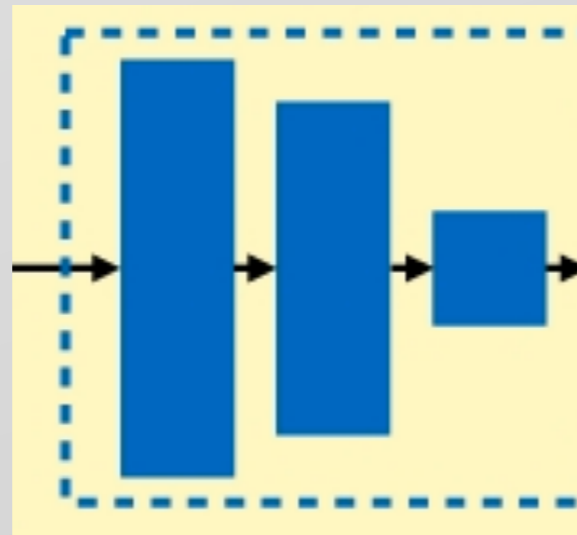
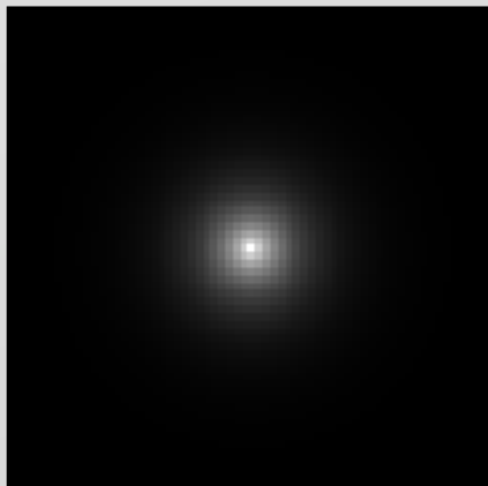


# Autoencoder

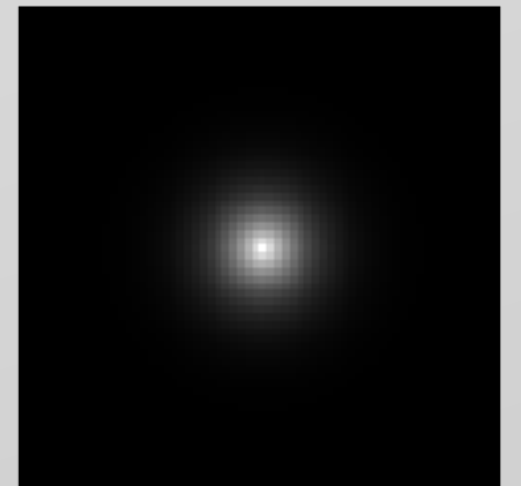


# Autoencoder

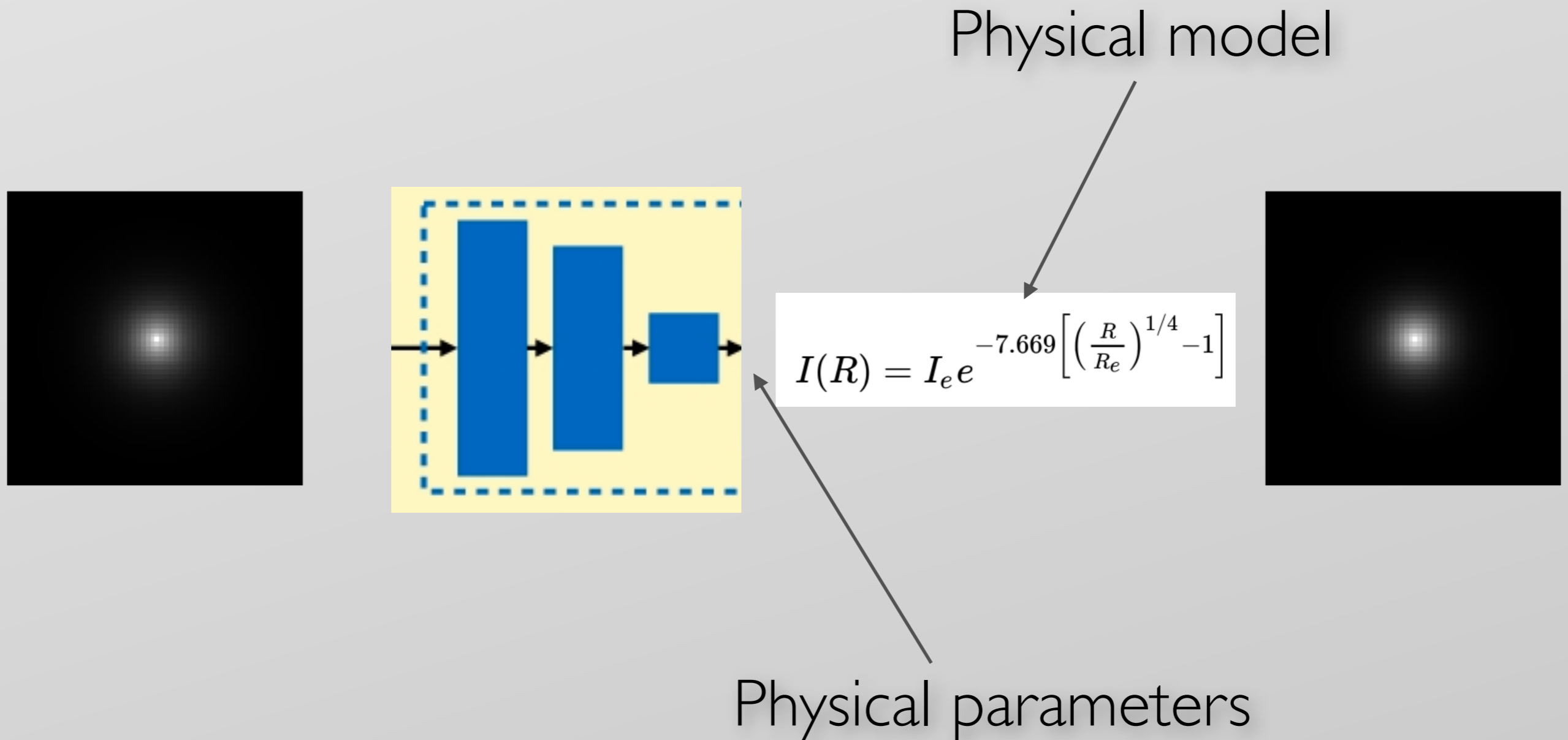
## Differentiable programming



$$I(R) = I_e e^{-7.669 \left[ \left( \frac{R}{R_e} \right)^{1/4} - 1 \right]}$$

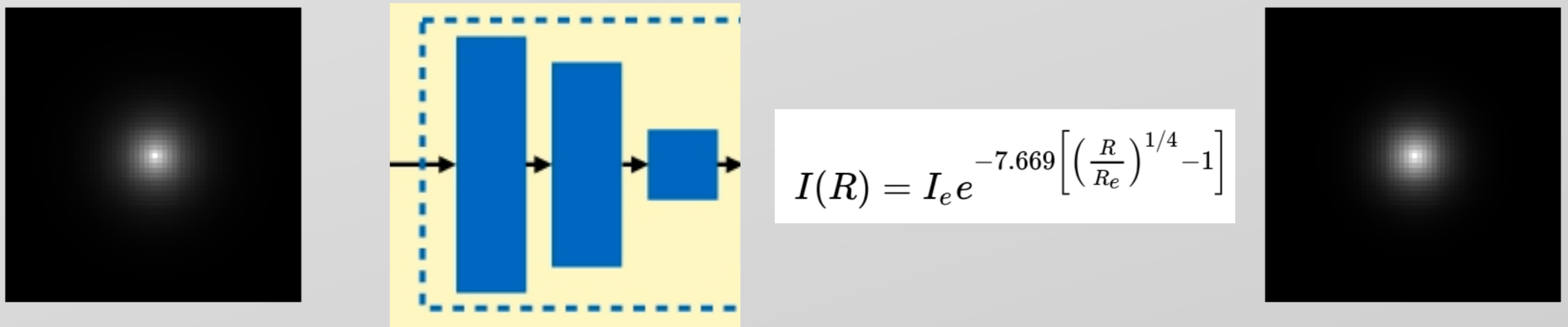


# Parametric autoencoder





# Parametric autoencoder



Sparse and semantic representation

Unsupervised

Perfect for recovering initial conditions

