What Did My CNN Learn?

-- an attempt to extract information from trained convolutional neural networks

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Battelle Job Interview - Data Scientist III

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Outline

What Did My CNN Learn?

0. My background

I. Motivation and Introduction to CNN

II. The approaches
   1. Visualize intermediate activations
   2. My CNN encoder and interpreters – some hybrid models
   3. Did my CNN learn translational symmetry?

III. Conclusion

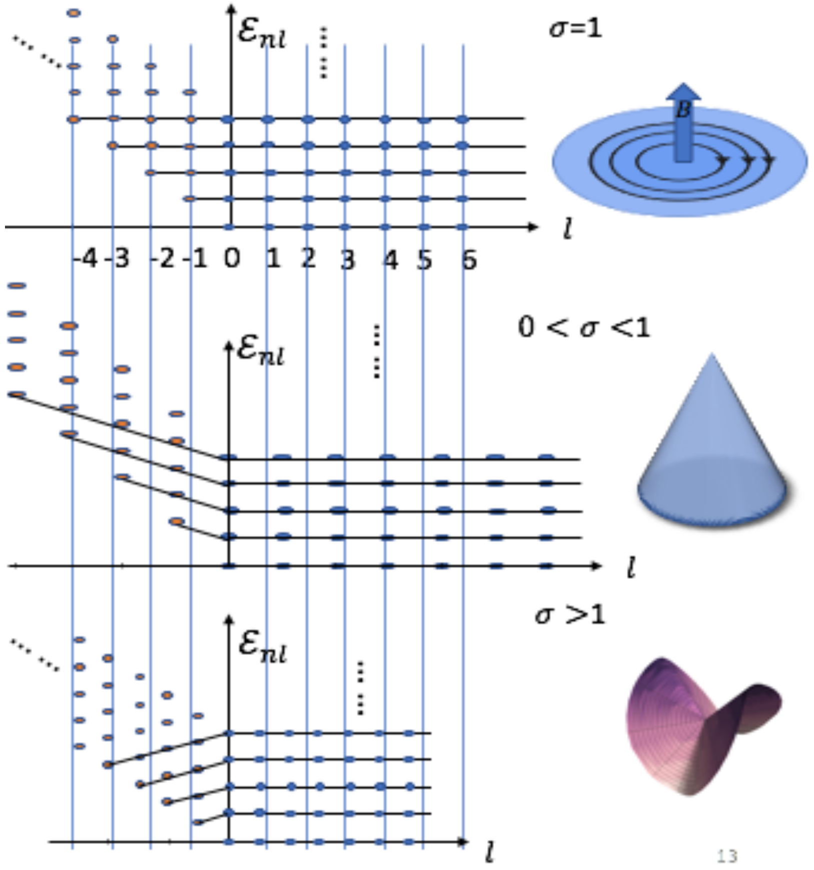
My Background

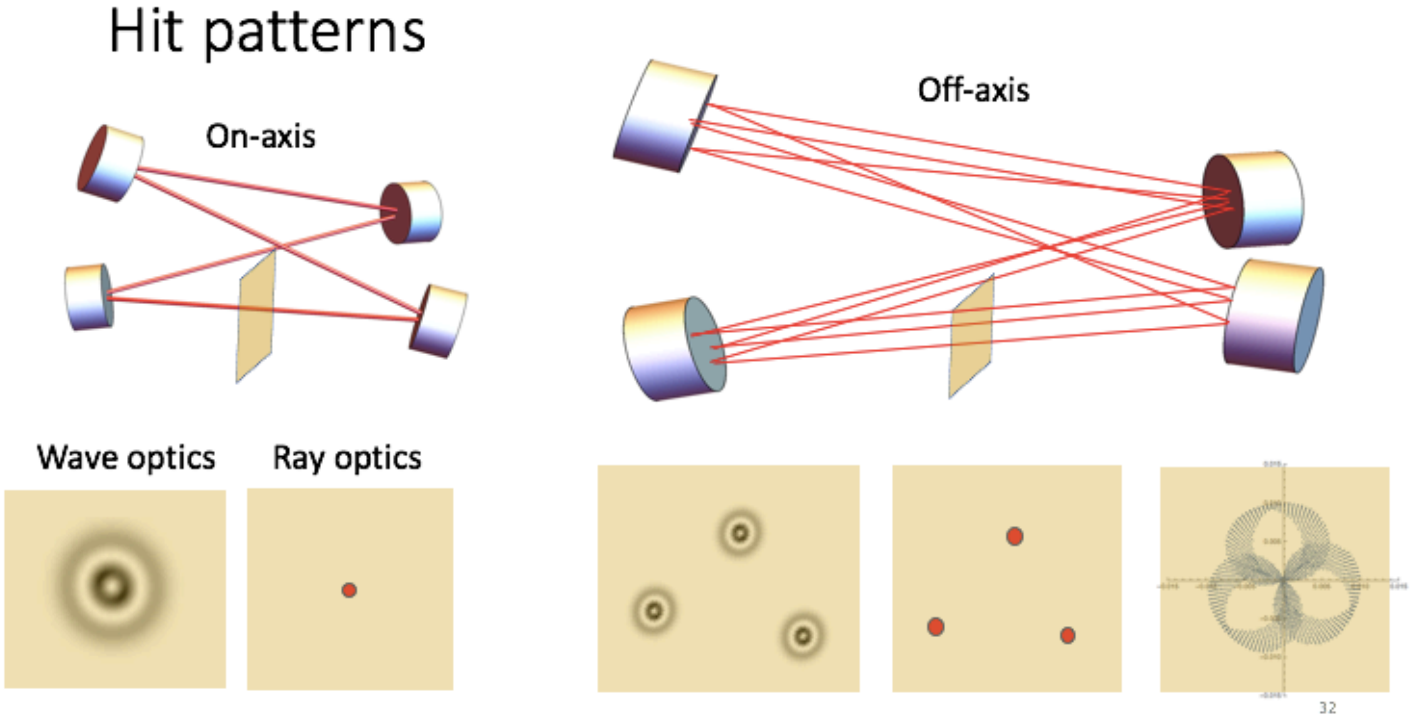
1. PhD research in Physics
2. Machine learning engineer intern

My background-I

The Ohio State University

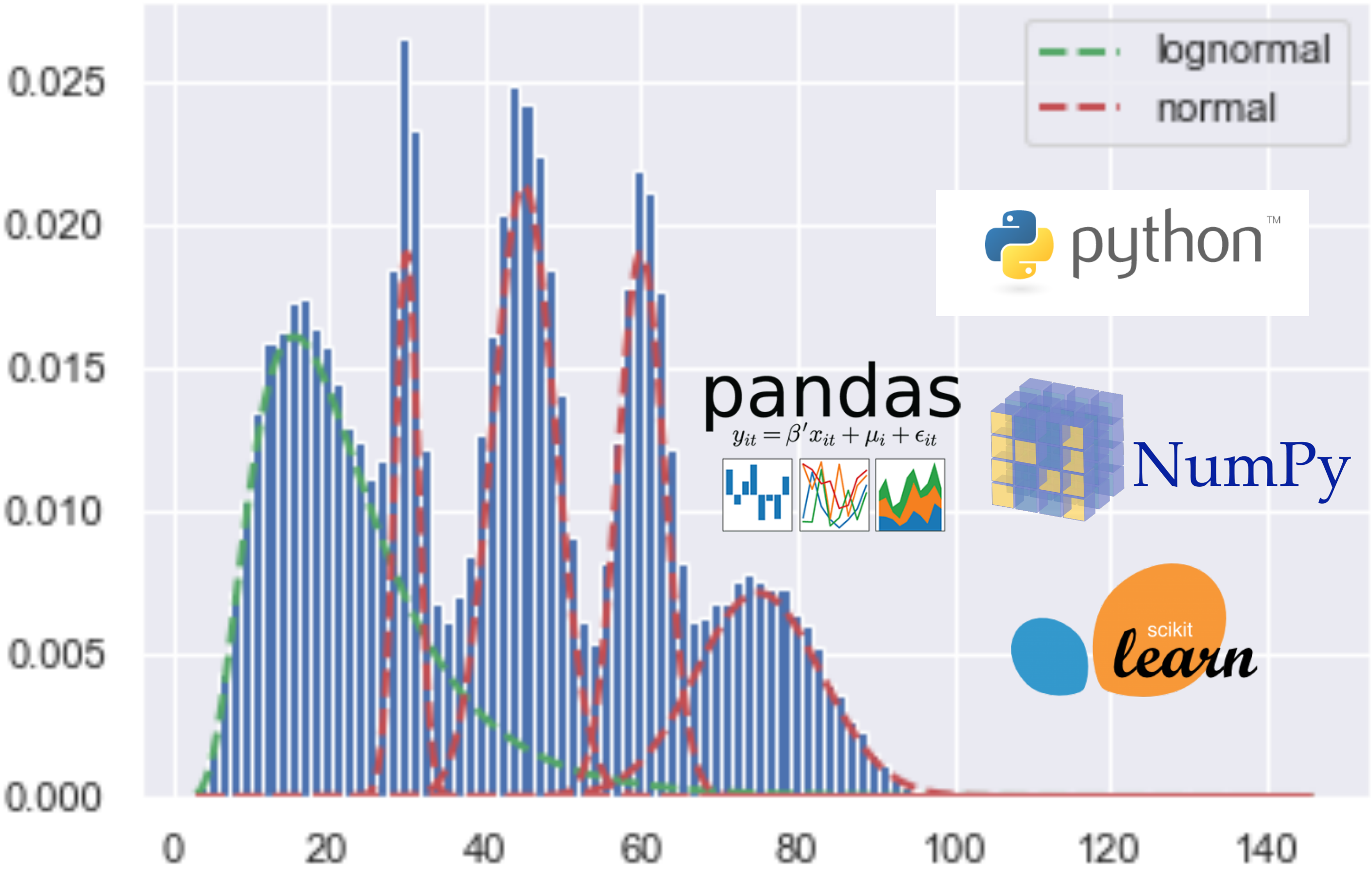
- My PhD in Physics, 2013-2018
  - Geometry and symmetry of quantum Hall physics with ultra-cold atoms and Laser
  - Discovered a novel quantum Hall phenomenon in Laser system





My background-II

- Machine Learning Engineer Intern, Owens Corning, 2018
  - Parametrize custom mixture model with normal and log-normal
  - Automate data cleansing, parsing, lag-time aggregation

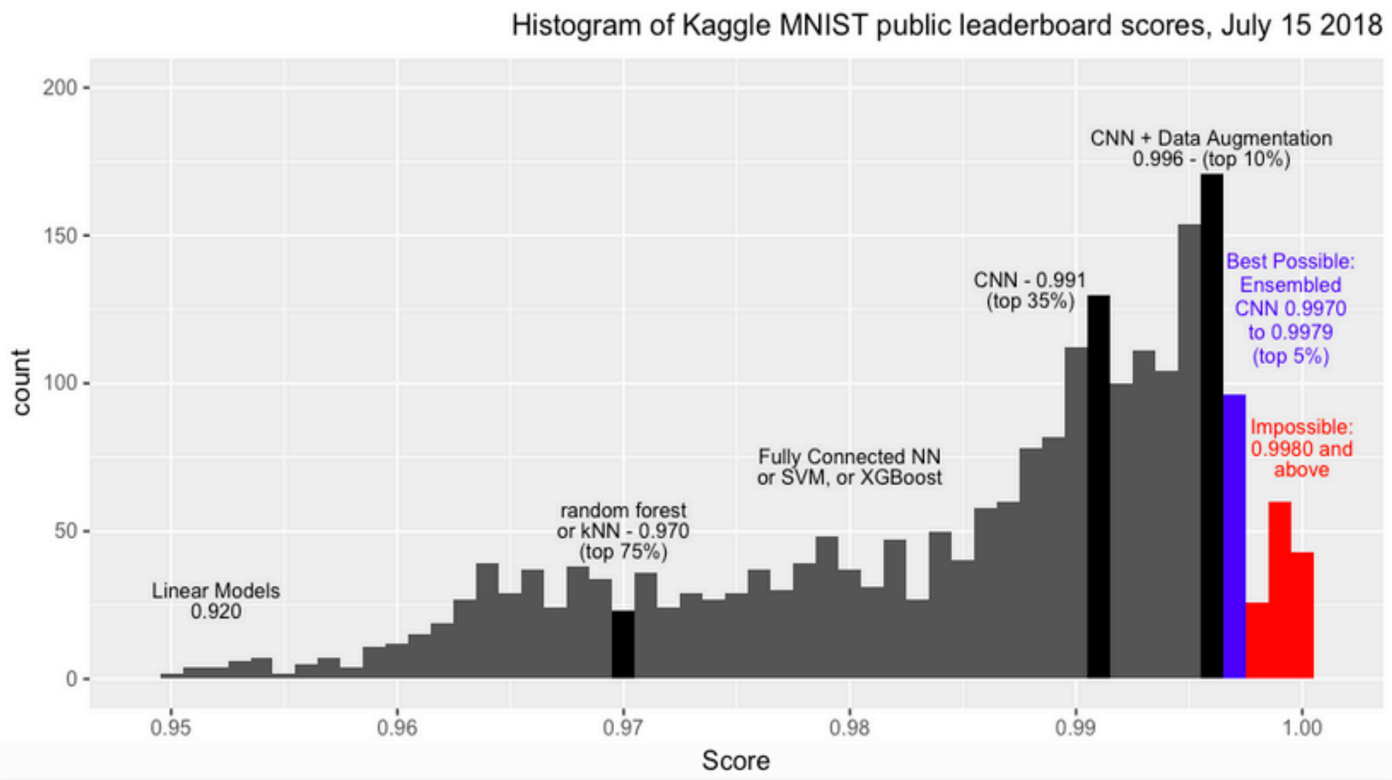


I. Motivation and Introduction to CNN

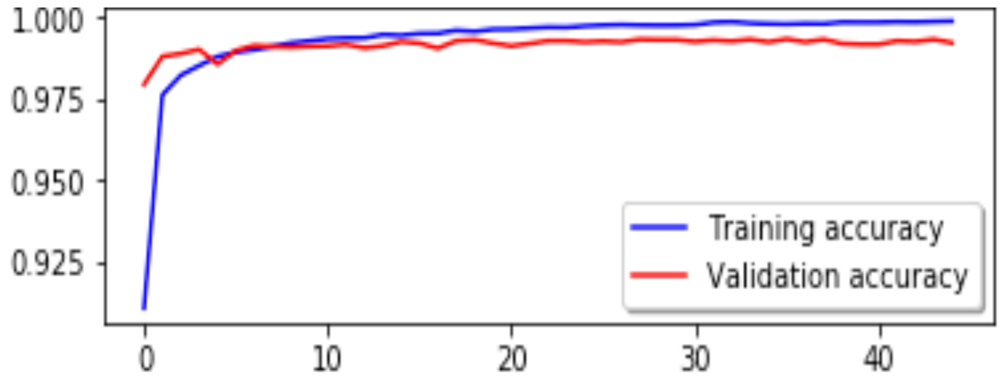
1. Motivation
2. Neural network
3. Convolutional network

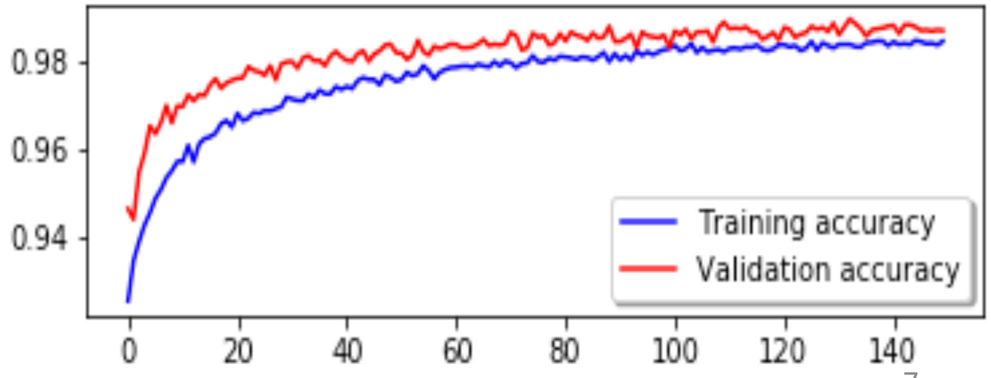
Motivation

1. My CNN classifier achieved 99.3% accuracy on MNIST hand-written digit data test set, but I cannot interpret it!
2. Knowing the information it did/did not learn can be the key to improvements.
3. *Validation accuracy exceeds training accuracy after data augmentation!*



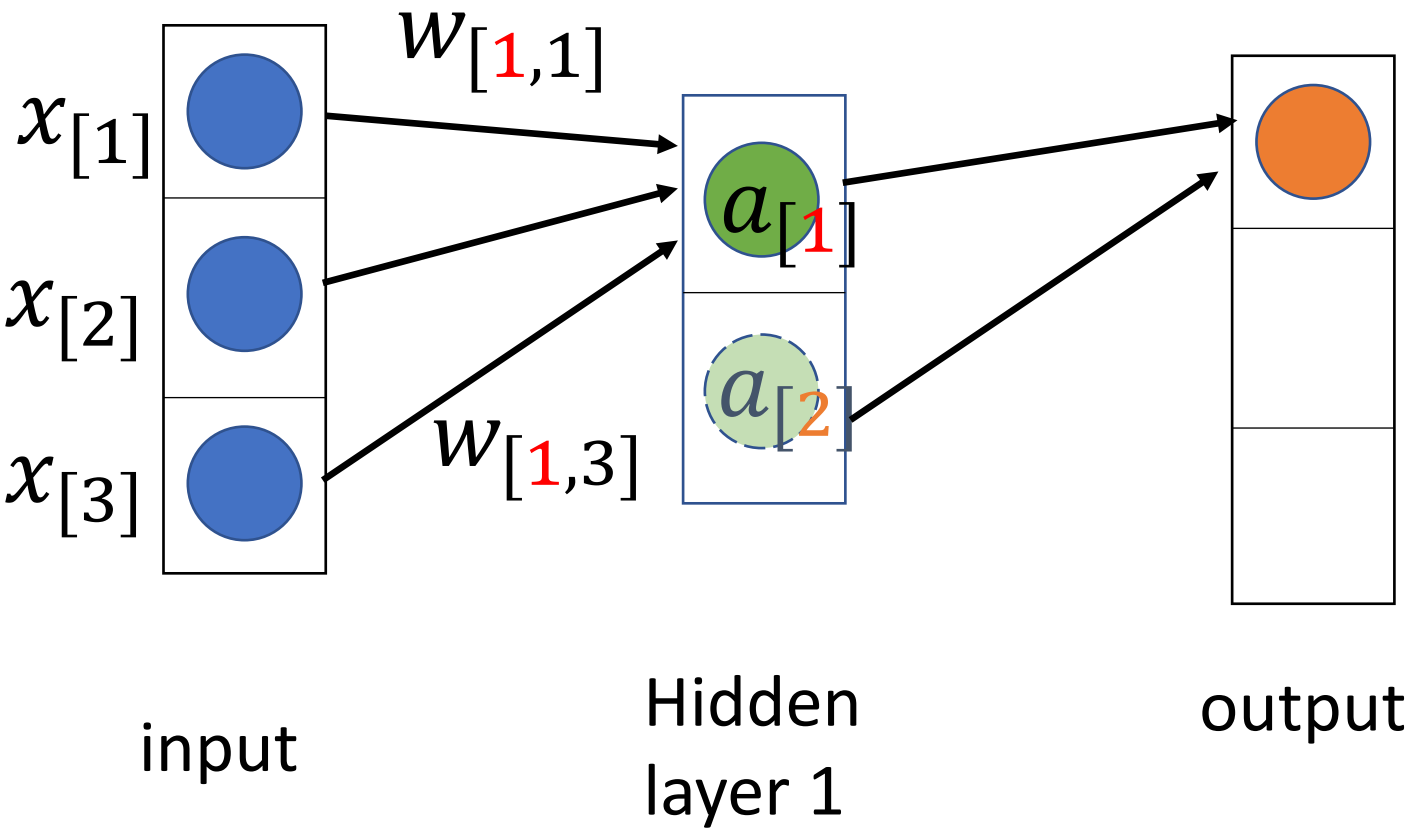
https://www.kaggle.com/cdeotte/25-million-images-0-99757-mnist





Neural network

$$a_{[1]} = \sigma\left(w_{[1,1]}x_{[1]} + w_{[1,2]}x_{[2]} + w_{[1,3]}x_{[3]} + b_{[1]} \cdot 1\right)$$



σ: activation function, nonlinear

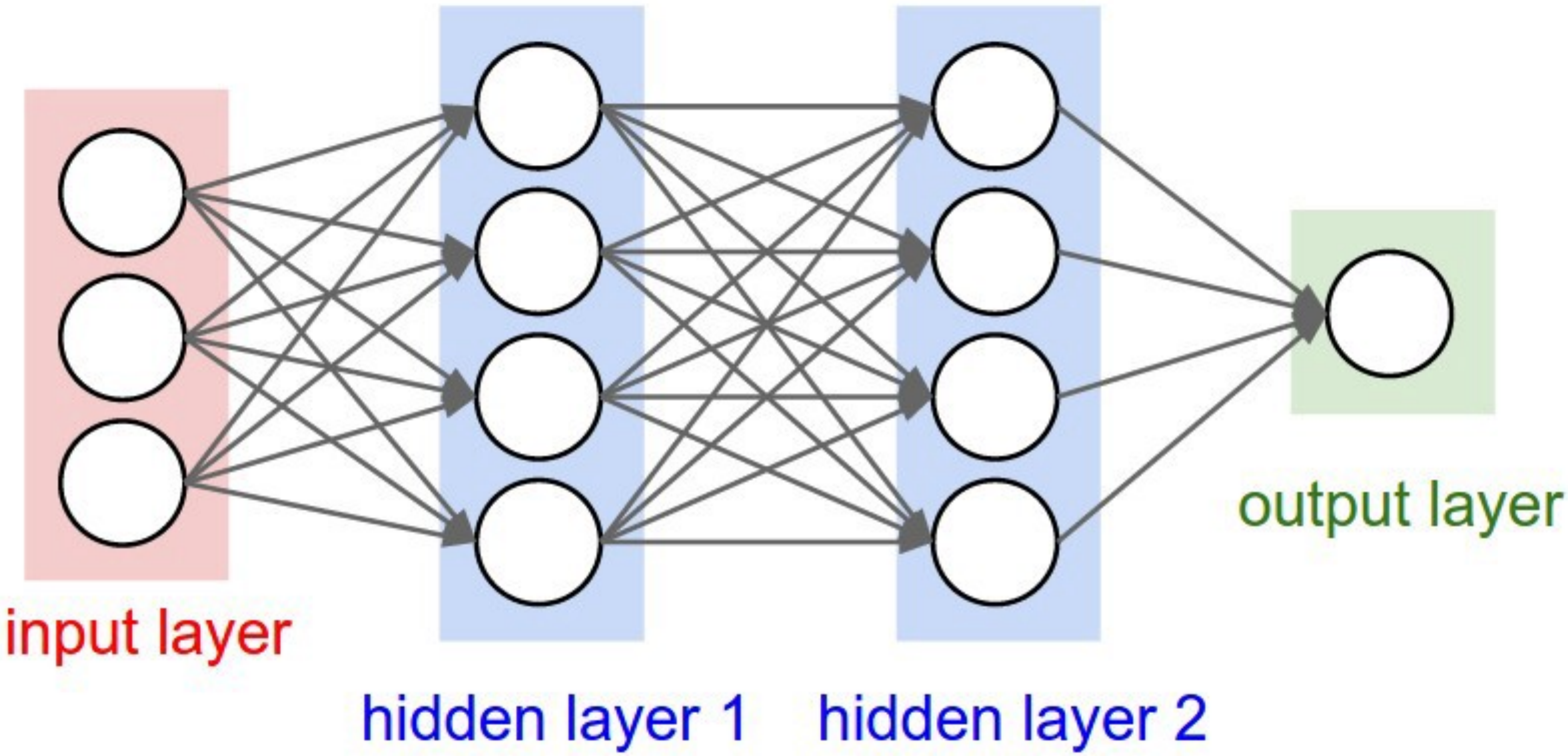
$$\vec{a} = \sigma\left(\overleftrightarrow{w} \cdot \vec{x} + \vec{b}\right)$$

$$\vec{a}^{(1)} = \sigma\left(\overleftrightarrow{w}^{(1)} \cdot \vec{x} + \vec{b}^{(1)}\right)$$

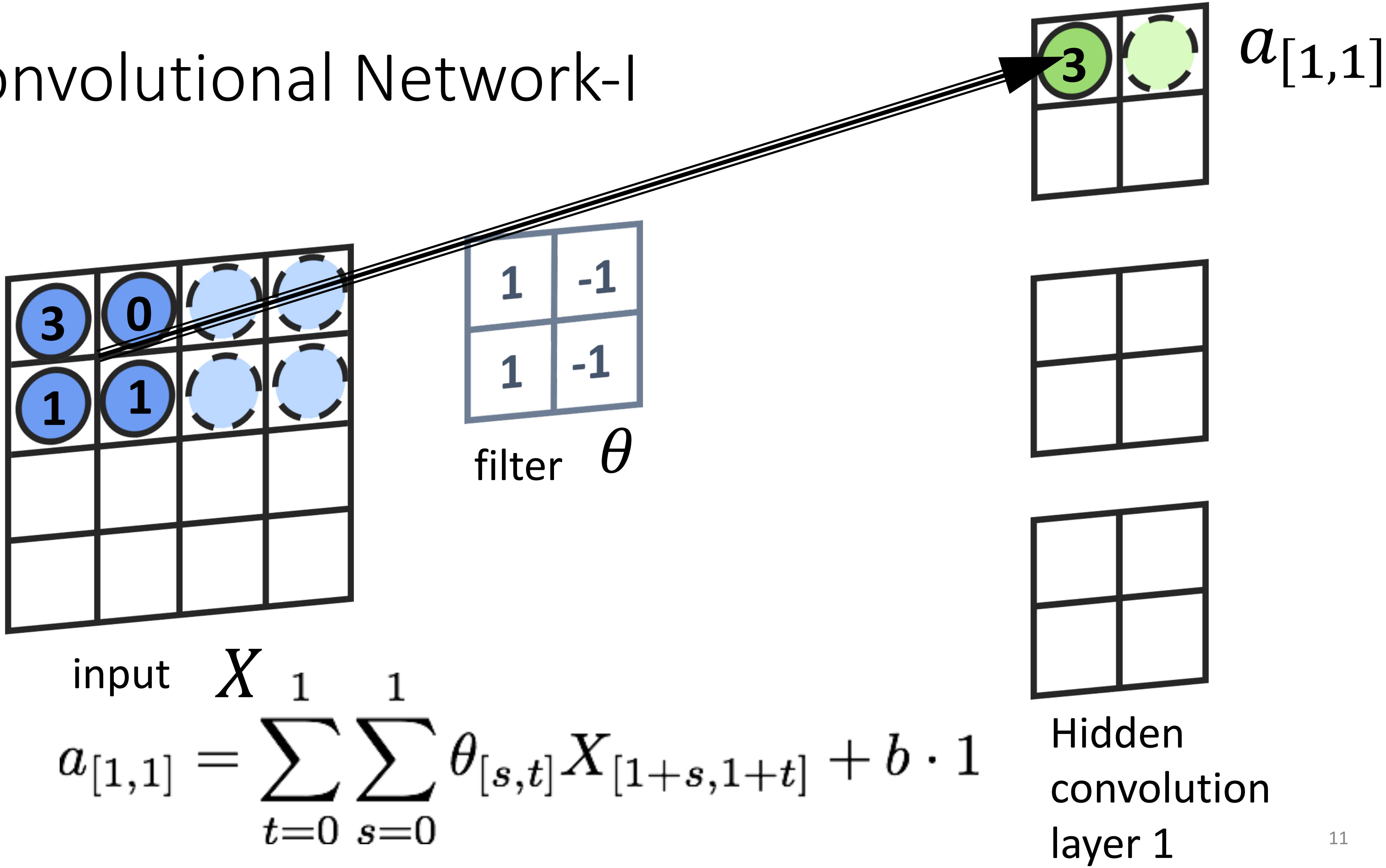
$$\vec{a}^{(2)} = \sigma\left(\overleftrightarrow{w}^{(2)} \cdot \vec{a}^{(1)} + \vec{b}^{(2)}\right)$$

$$\vec{a}^{(h)} = \sigma\left(\overleftrightarrow{w}^{(h)} \cdot \vec{a}^{(h-1)} + \vec{b}^{(h)}\right)$$

Neural Network – fully connected network



Convolutional Network-I

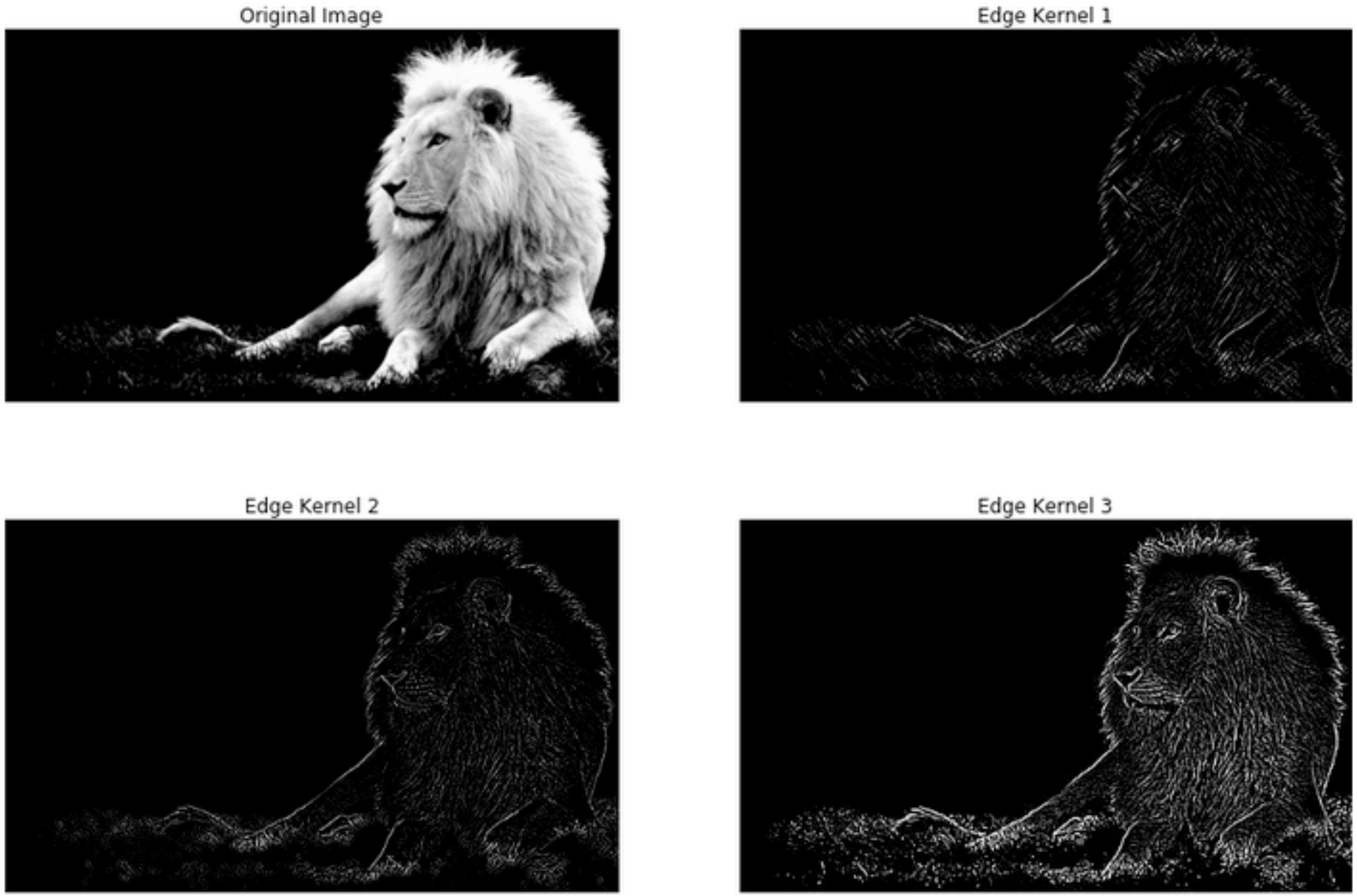


$$a_{[1,1]} = \sum_{t=0}^{1} \sum_{s=0}^{1} \theta_{[s,t]} X_{[1+s,1+t]} + b \cdot 1$$

Convolution

- Convolution can do edge detection, blurring, sharpening and etc.

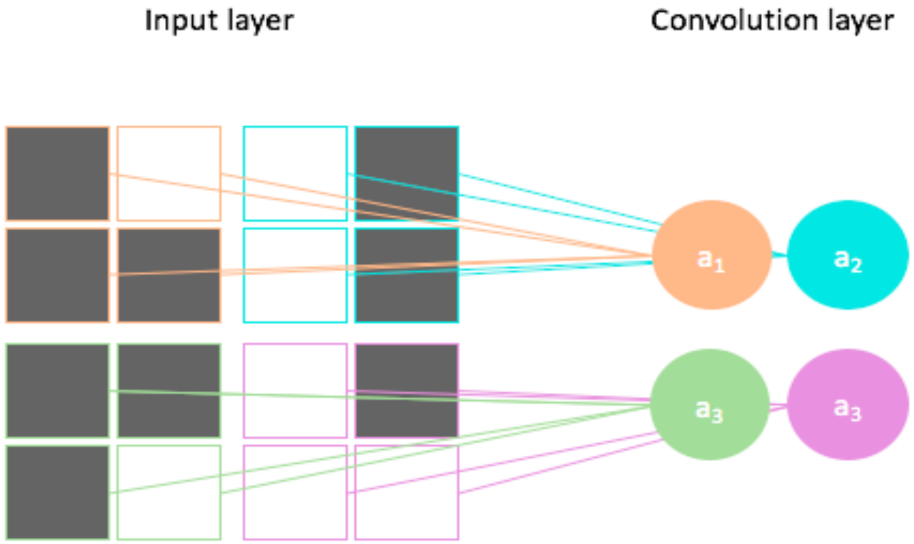
```
edge_kernel_1 = np.array([[1, 0, -1],
                          [0, 0, 0],
                          [-1, 0, 1]])

edge_kernel_2 = np.array([[0, 1, 0],
                          [1, -4, 1],
                          [0, 1, 0]])

edge_kernel_3 = np.array([[-1, -1, -1],
                          [-1, 8, -1],
                          [-1, -1, -1]])
```

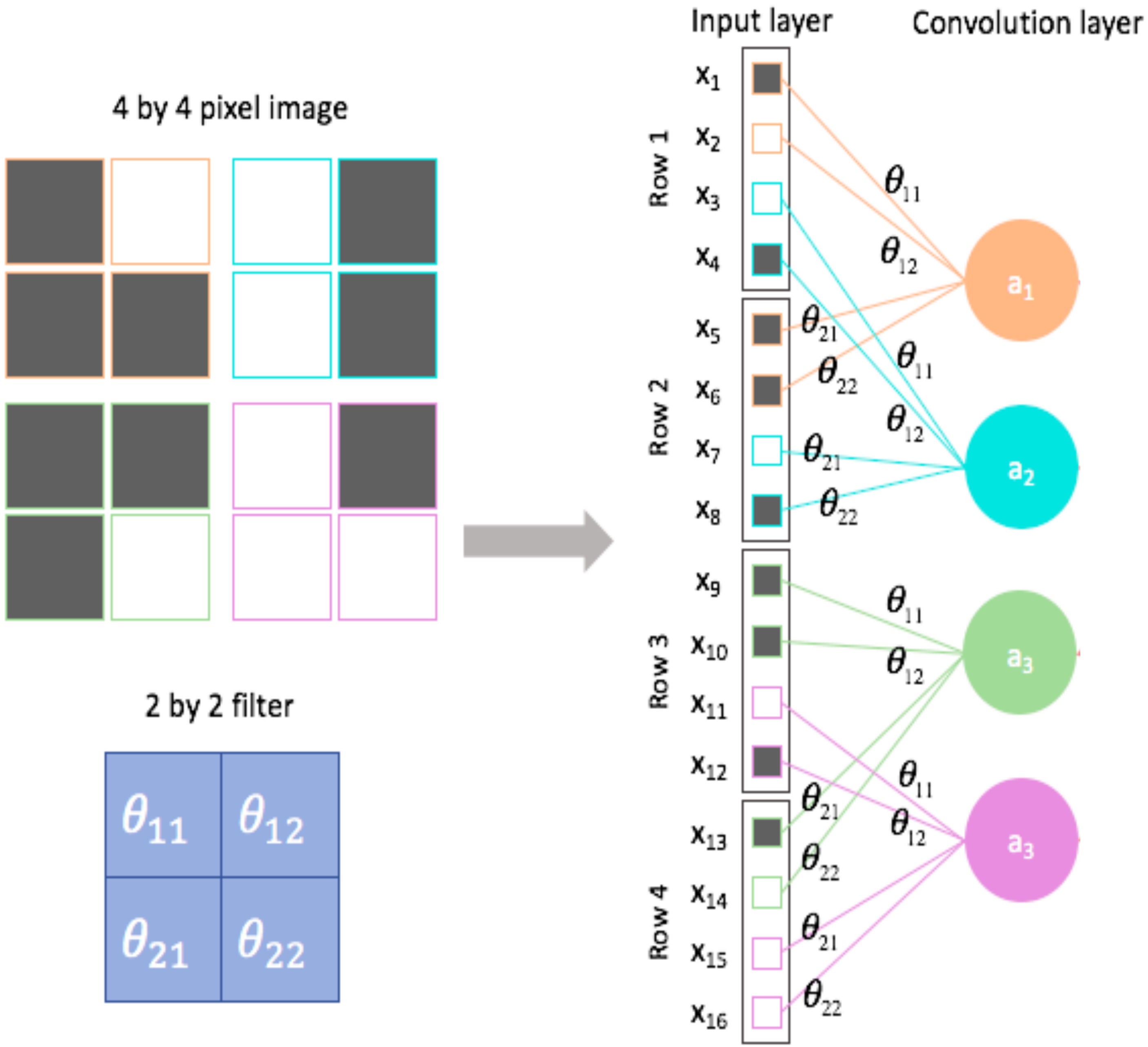


https://beckernick.github.io/convolutions/

Conv Net-II

1. Locality is preserved with convolution
2. Sparsely connected NN





https://www.jeremyjordan.me/convolutional-neural-networks/

The approaches

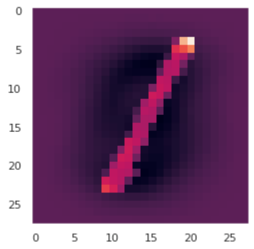
1. Visualize the intermediate activations
2. CNN encoder and interpreters
3. Did my CNN learn translational symmetry?

Visualize the intermediate activations-I

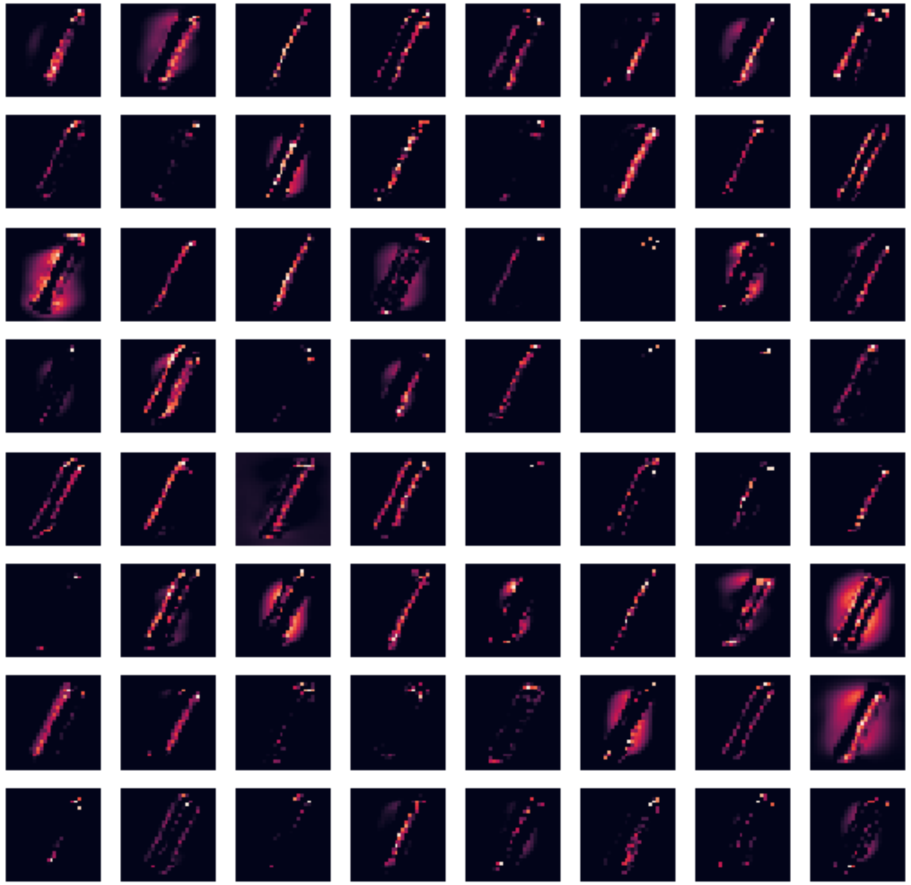
h:hiddne layer index

conv2d_1 $h = 1$

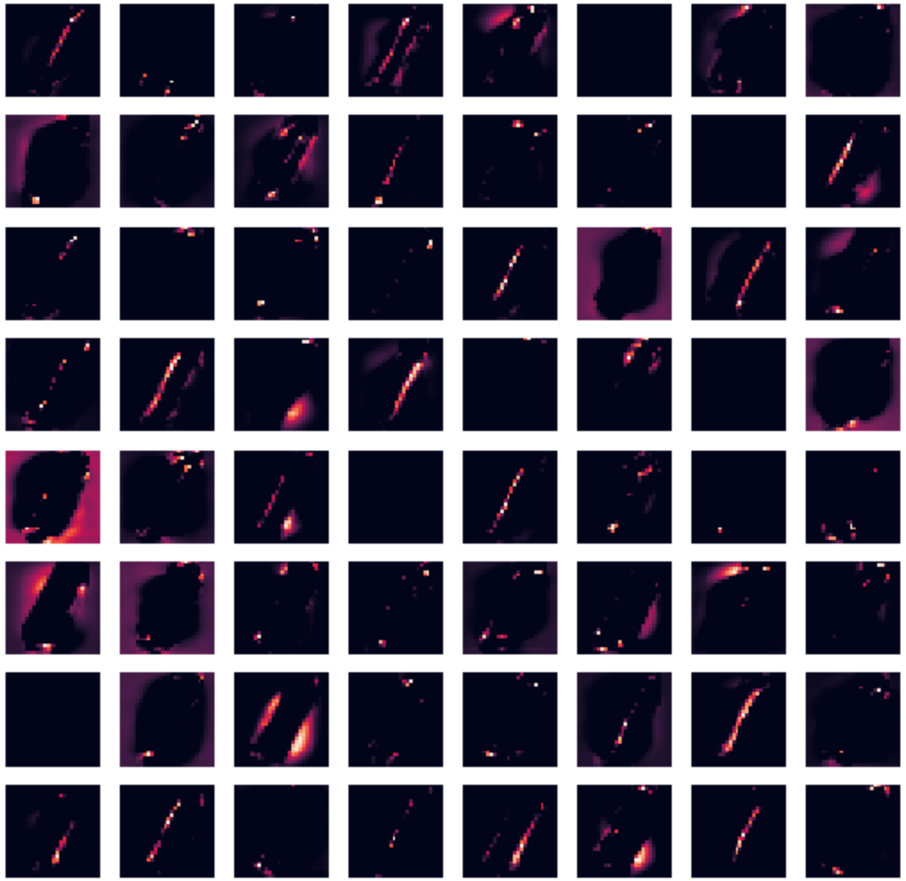
conv2d_2 $h = 2$



28*28=784



(28*28)*64=50,176



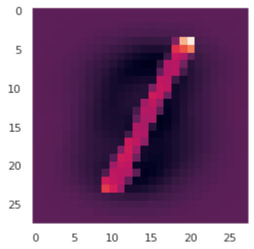
(28*28)*64=50,176

Visualize the intermediate activations-II

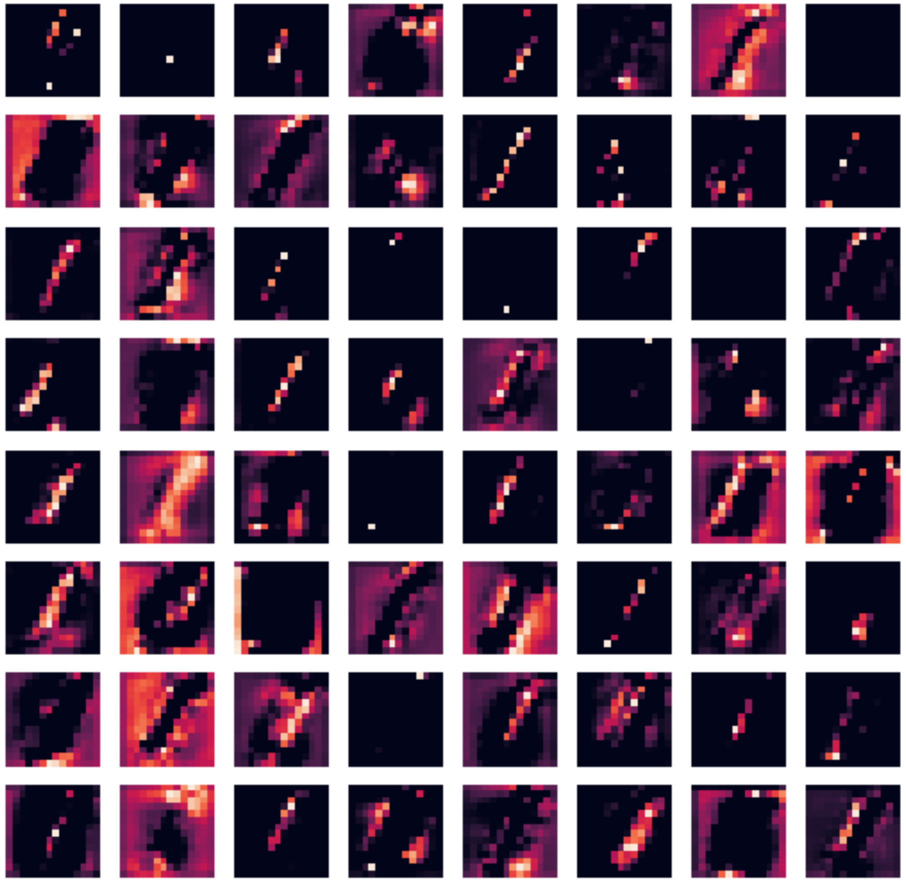
h:hiddne layer index

conv2d_3 $h = 5$

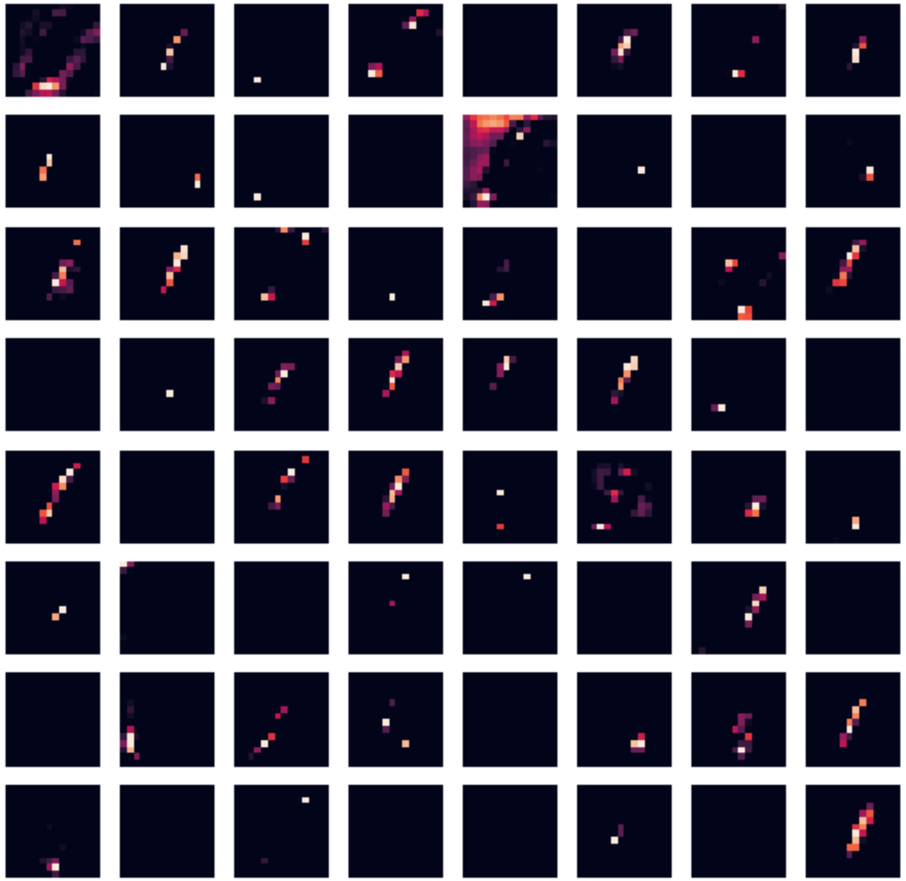
conv2d_4 $h = 6$



28*28=784



(14*14)*64=12,544

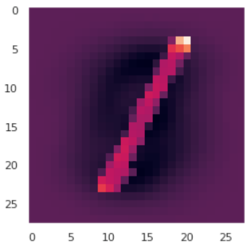


(14*14)*64=12,544

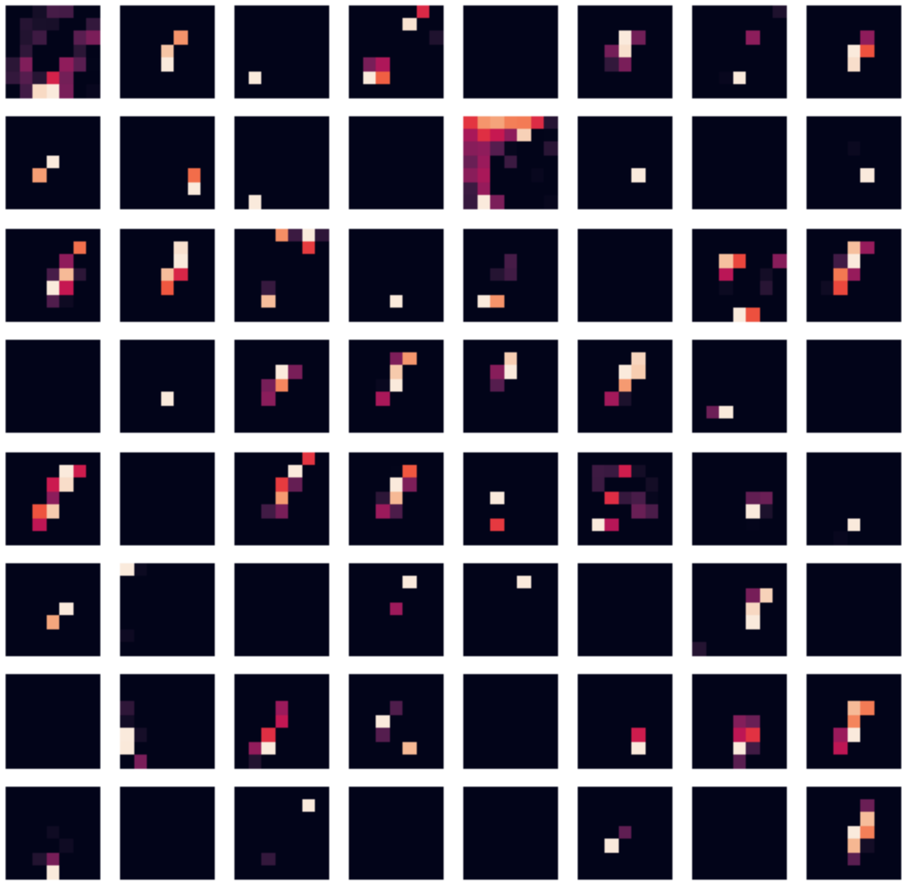
Visualize the intermediate activations-III

h:hiddne layer index

dropout_2 $h = 8$

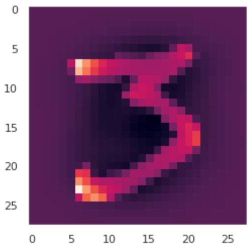


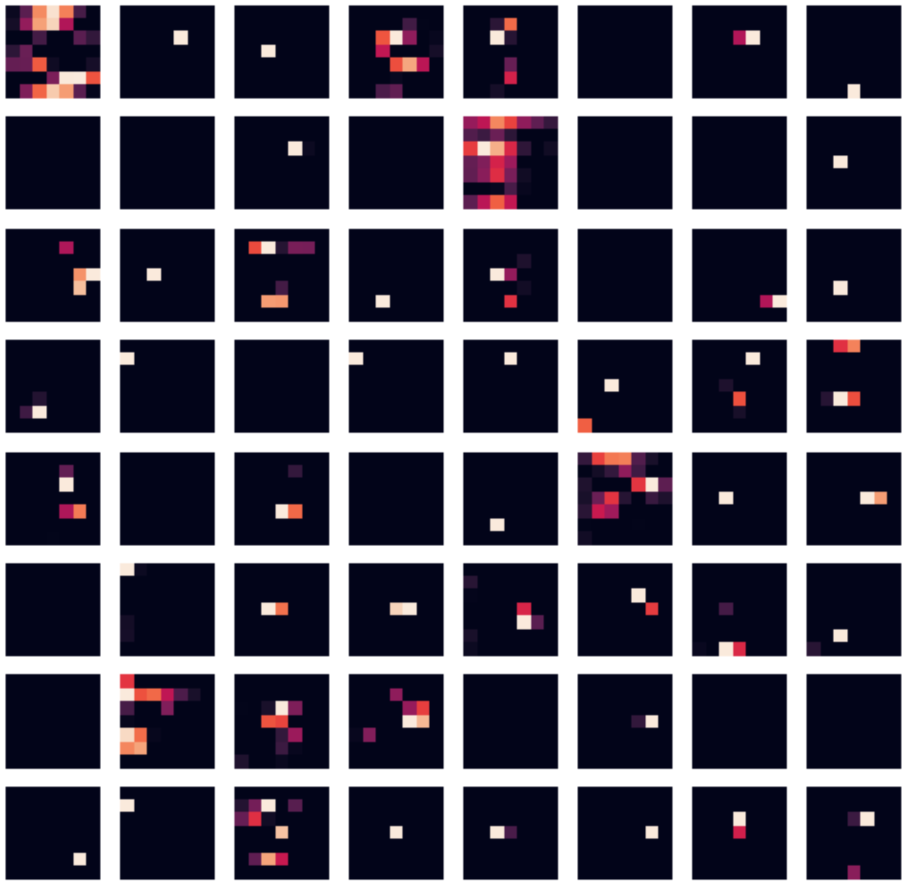
28*28=784



(7*7)*64=3,136

dropout_2 $h = 8$





(7*7)*64=3,136

CNN encoder and interpreters

the architecture

```
#The model structure
my_CNN_clf=Sequential([
    ############################## CNN-encoder
    Conv2D(filters = 64, activation = 'relu',kernel_size=(5,5),padding='Same',input_shape = (28,28,1)),
    Conv2D(filters = 64, activation = 'relu',kernel_size=(5,5),padding='Same'),
    MaxPool2D(pool_size=(2,2),strides=(2,2)),
    Dropout(0.25),
    Conv2D(filters = 64, activation = 'relu',kernel_size=(3,3),padding='Same'),
    Conv2D(filters = 64, activation = 'relu',kernel_size=(3,3),padding='Same'),
    MaxPool2D(pool_size=(2,2),strides=(2,2)),
    Dropout(0.25),
    Flatten(), # d=64*7*7=3136
    ############################## CNN-encoder

    ##################           compressor
    Dense(256, activation='relu'),
    Dropout(0.5), #d = 256
    ##################           compressor

    ############################## interpretor
    Dense(10, activation='softmax'), #a normalized exponential functions for probability
    ############################## interpretor
    ])
```

$h = 1$
$h = 2$

$h = 5$
$h = 6$

$h = 8$

Encoder: input→ 3,136-dimensional vector

$h = 10$

Compressor: 3,136 → 256 dimensional

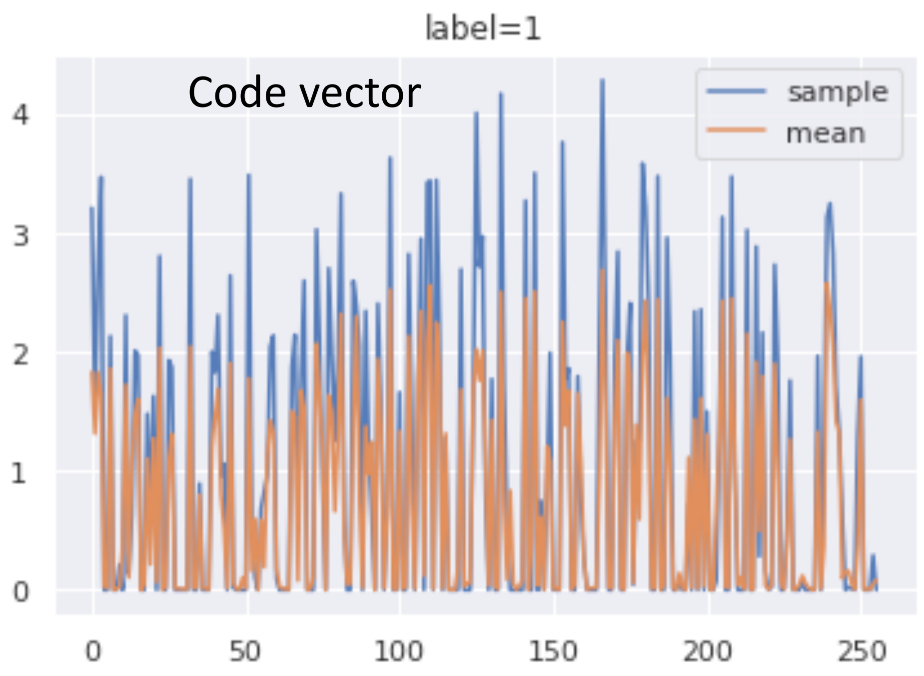
The code vector

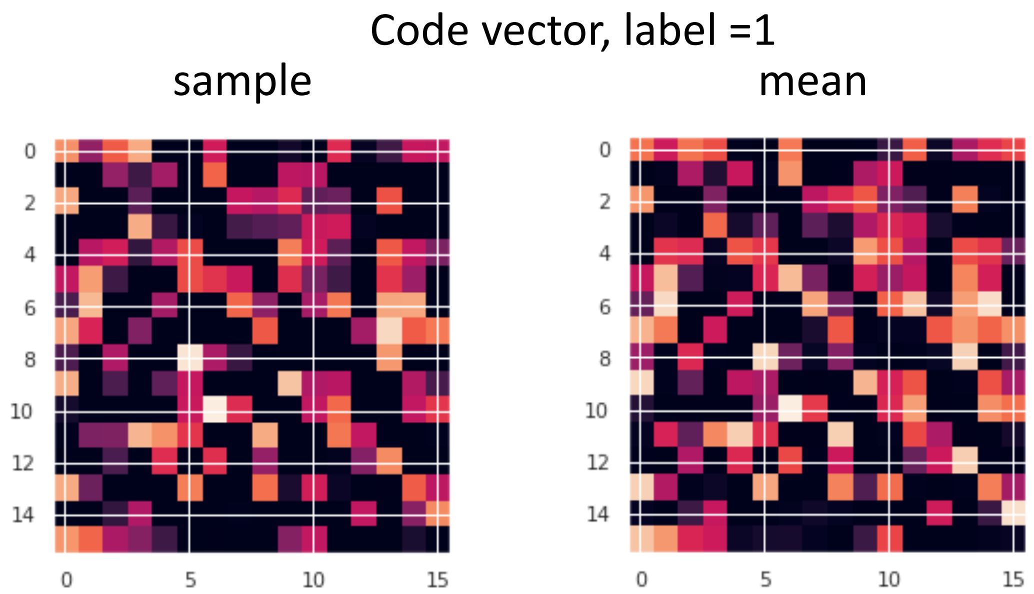
Interpreter: 256 → 10 dim. probability vector for predictions

CNN encoder and interpreters
the code vectors

1. Consistent and self-similarity within a class(both code vectors and probabilities)
2. Different interpreters show similar accuracy
   => encoder is the key for acc.

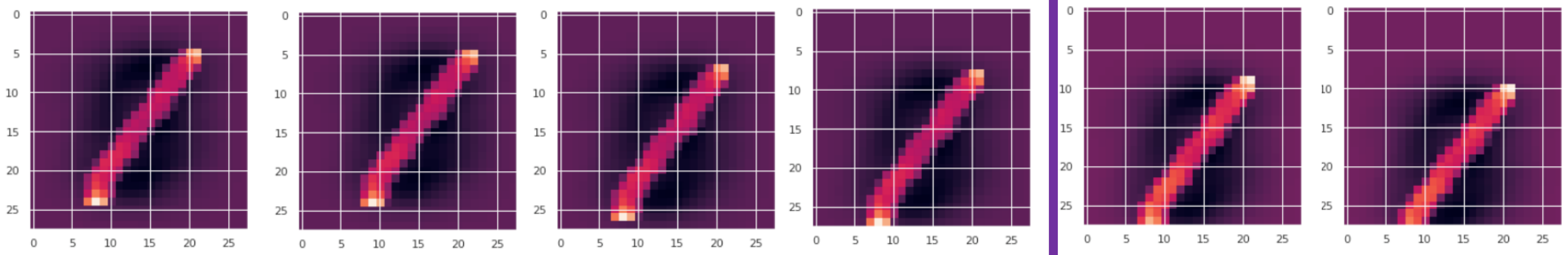
Interpreters	accuracy
1 Dense layer NN	99.44%
SVM	99.35%
Random Forests (100 trees)	99.32%
Gradient Boost (100 trees)	99.24%
Decision Tree	98.46%





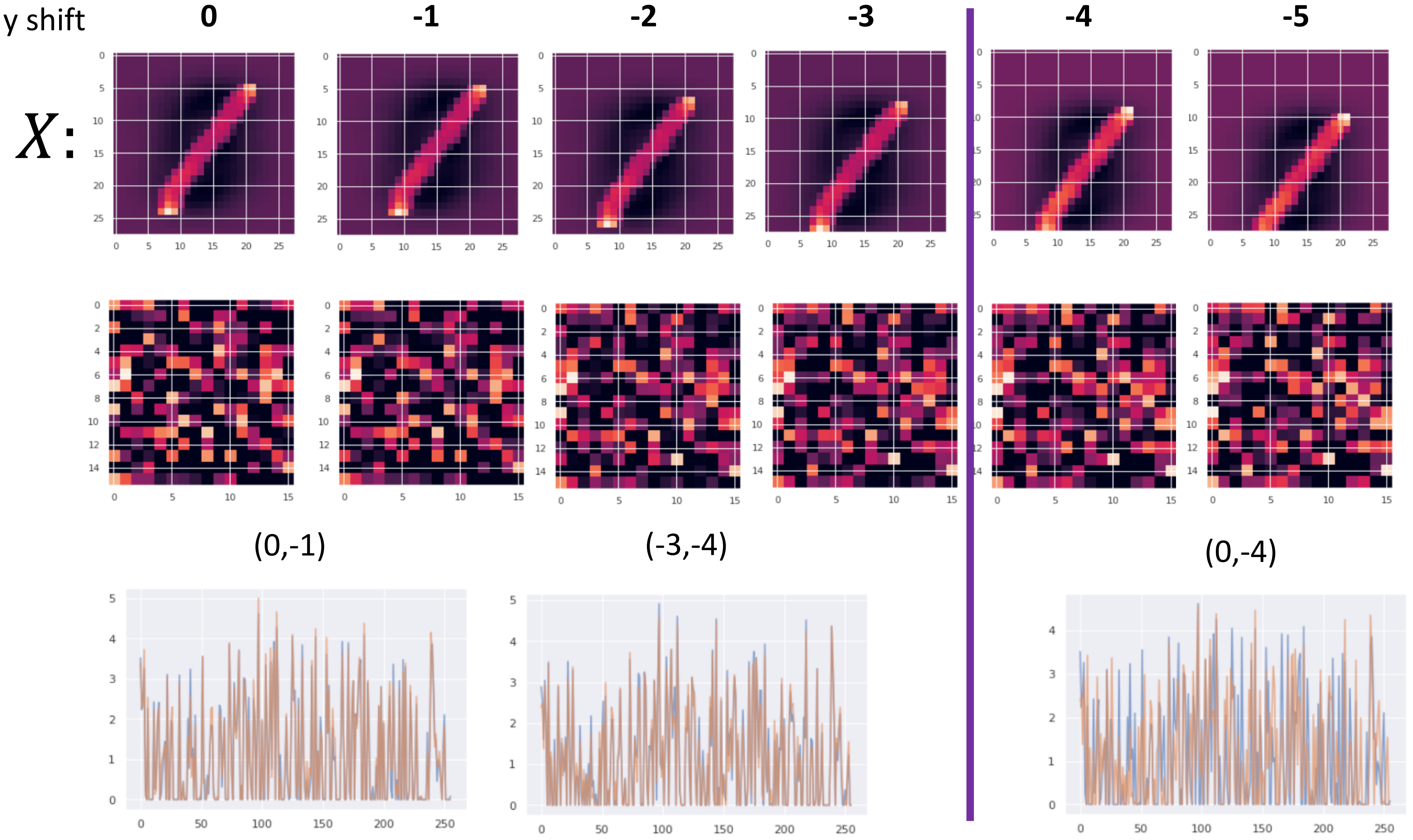
Did my CNN learn translational symmetry?

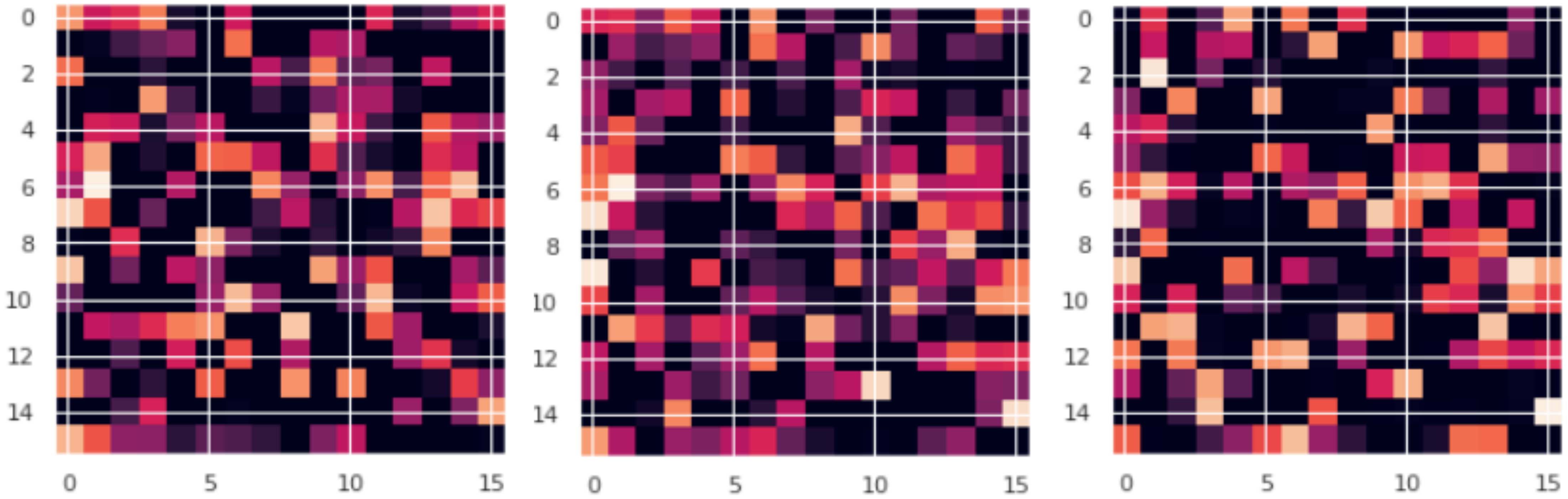
$Prob(y = 1|X)$ X:



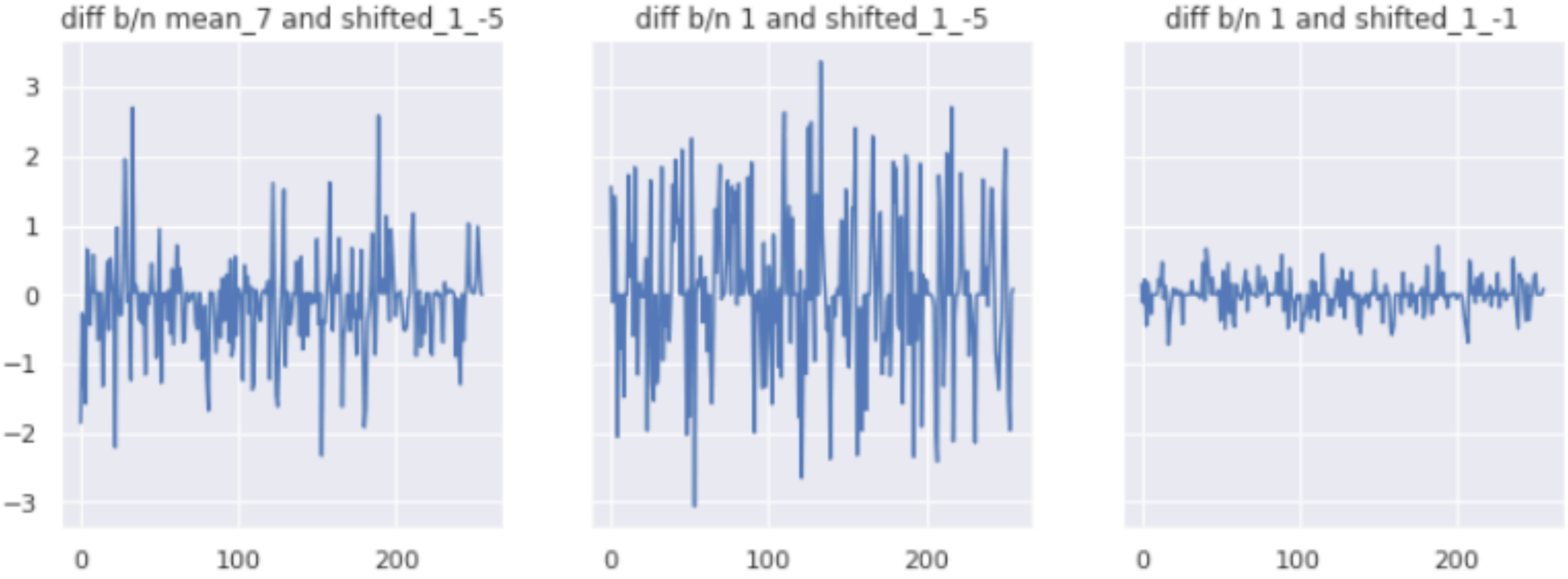
y shift (pixels)	0	-1	-2	-3	-4	-5
CNN (CNN+NN) (acc = 99.3%)	100%	100%	99.99%	99.4%	0.71% (7: 99.29%)	1.4E-4% (7: 99.99%)
Random Forest (RF) (acc = 96.6%)	99.5%	84.9% (7: 9.8%)	34.1% (7: 39.6%)	9.1% (7: 56.3%)	5.4% (7: 70.1%)	4.8% (7: 70.2 %)
SVM (acc = 96.1%)	99.6%	42.8% (7: 50.8%)	0.85% (7: 94.5%)	0.42% (7: 81.3 %)	0.43% (7: 79.5%)	0.42% (80.8%)
CNN+RF, T=1000 (acc = 99.3)	100%	96.6%	67.7% (7: 18.4)	52.8% (7: 28.3%)	44.4% (7: 35.5%)	34.8% (7: 47.6 %)
CNN+SVM (acc = 99.3%)	99.9%	99.8%	97.8%	79.9% (9: 18.8%)	21% (9: 77.76%)	1% (9: 98.9%)

Did my CNN learn translational symmetry?





0
2
4
6
8
10
12
14
0
5
10
15


diff b/n mean_7 and shifted_1_-5
diff b/n 1 and shifted_1_-5
diff b/n 1 and shifted_1_-1
3
2
1
0
−1
−2
−3
0
100
200

Conclusion

- Code vectors in hidden layers of CNN reduce the dimensionality of images.
- Information learned in CNN is **position sensitive**. And convolution is the key for high accuracy performance.
- The predicted probabilities of CNN are not continuous with respect to translations.
- Translations deform CNN code vectors more softly.