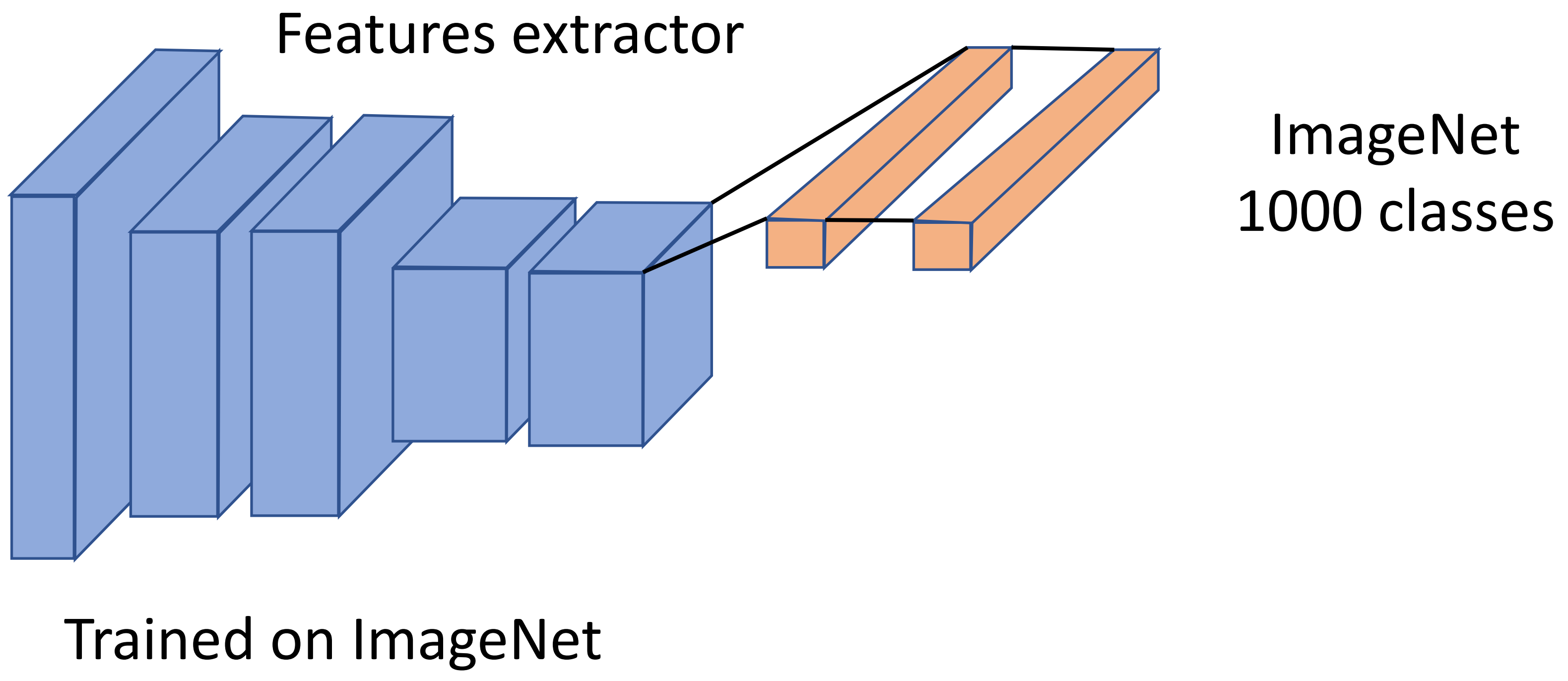
MML minor #7

Нейросети: transfer learning, другие CNN задачи и автокодировщики

Transfer learning

- Deep networks learn complex features extractor, but we need lots of data to train it from scratch!
- What if we can reuse an existing features extractor for a new task?



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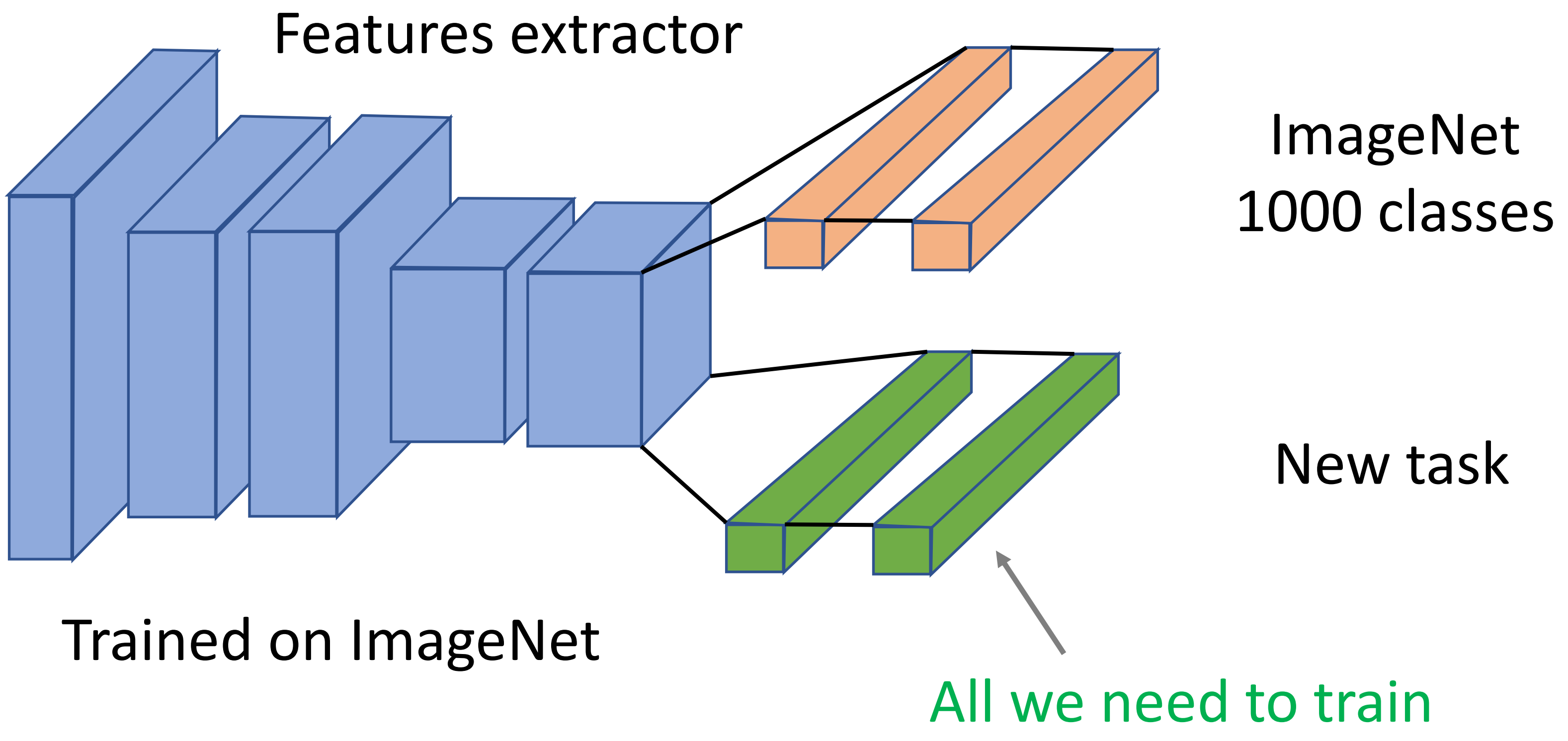


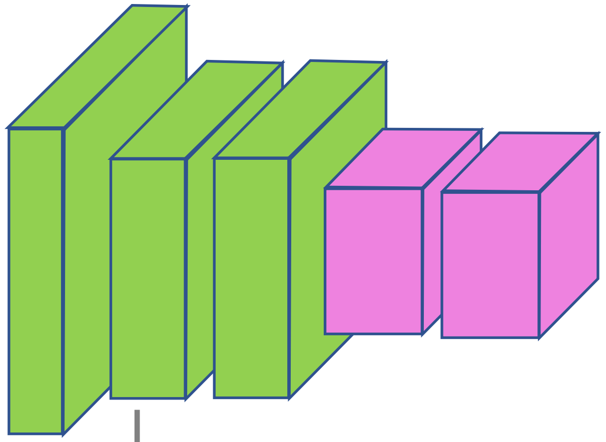
Transfer learning

- You need less data to train (for training only final MLP)
- It works if a domain of a new task is similar to ImageNet’s
- Won’t work for human emotions classification,
  ImageNet doesn’t have people faces in the dataset!

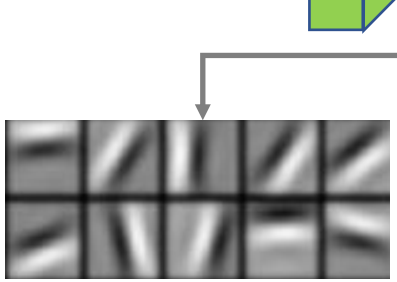
Transfer learning

- But what if we need to classify human emotions?
- Maybe we can partially reuse ImageNet features extractor?

Extractor
we want:



Activation
stimuli:



http://web.eecs.umich.edu/~honglak/icml09-ConvolutionalDeepBeliefNetworks.pdf

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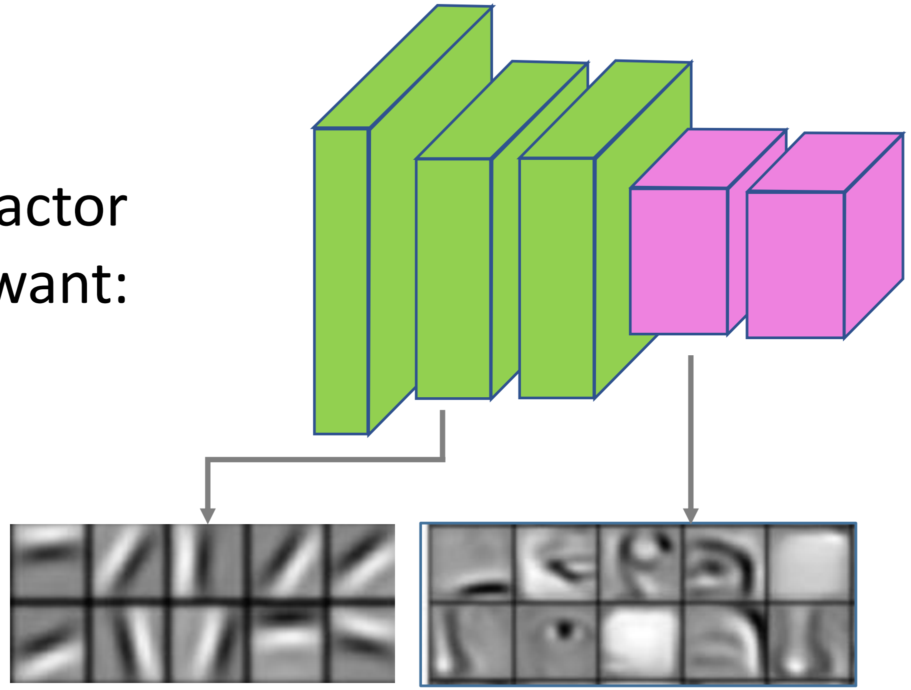
Activation stimuli:



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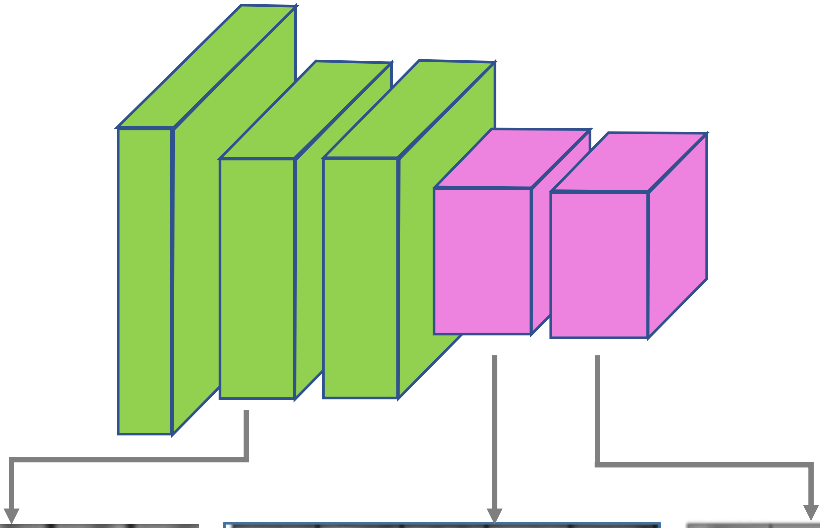

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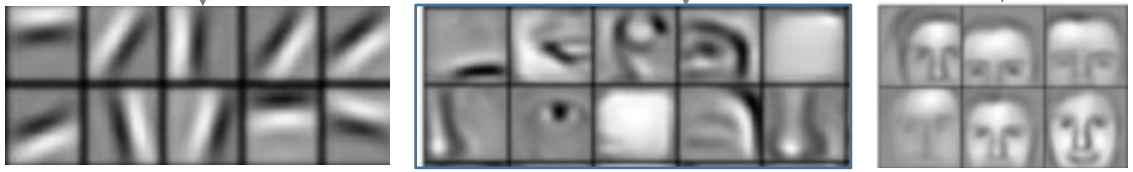

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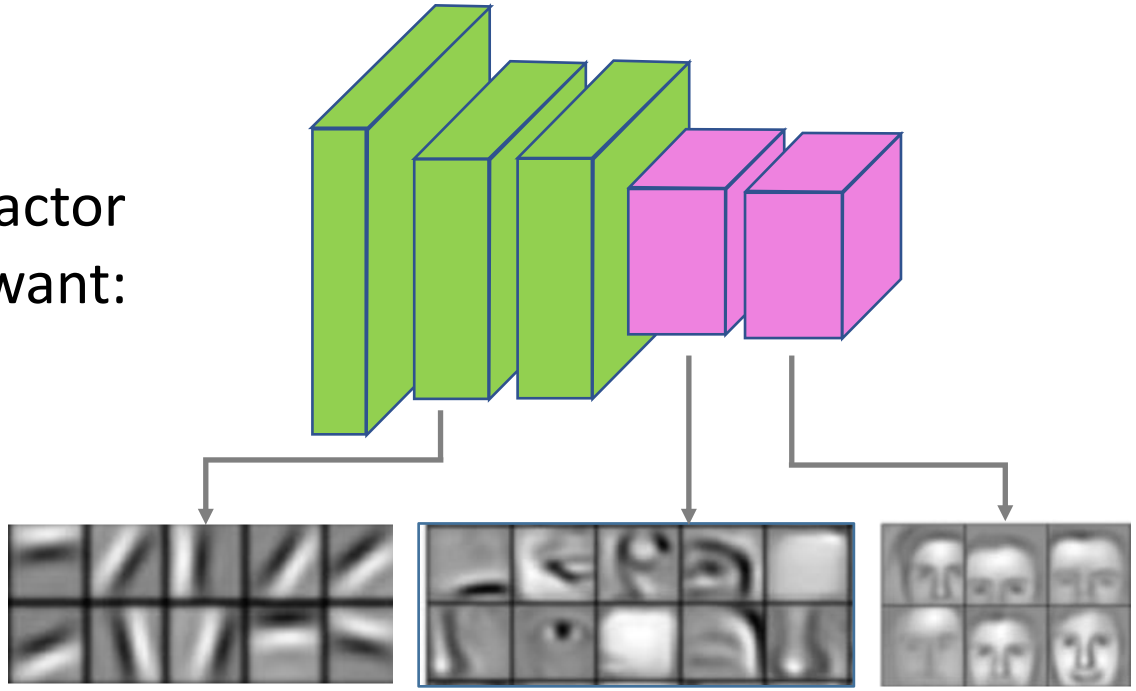

ImageNet
has this!

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Transfer learning

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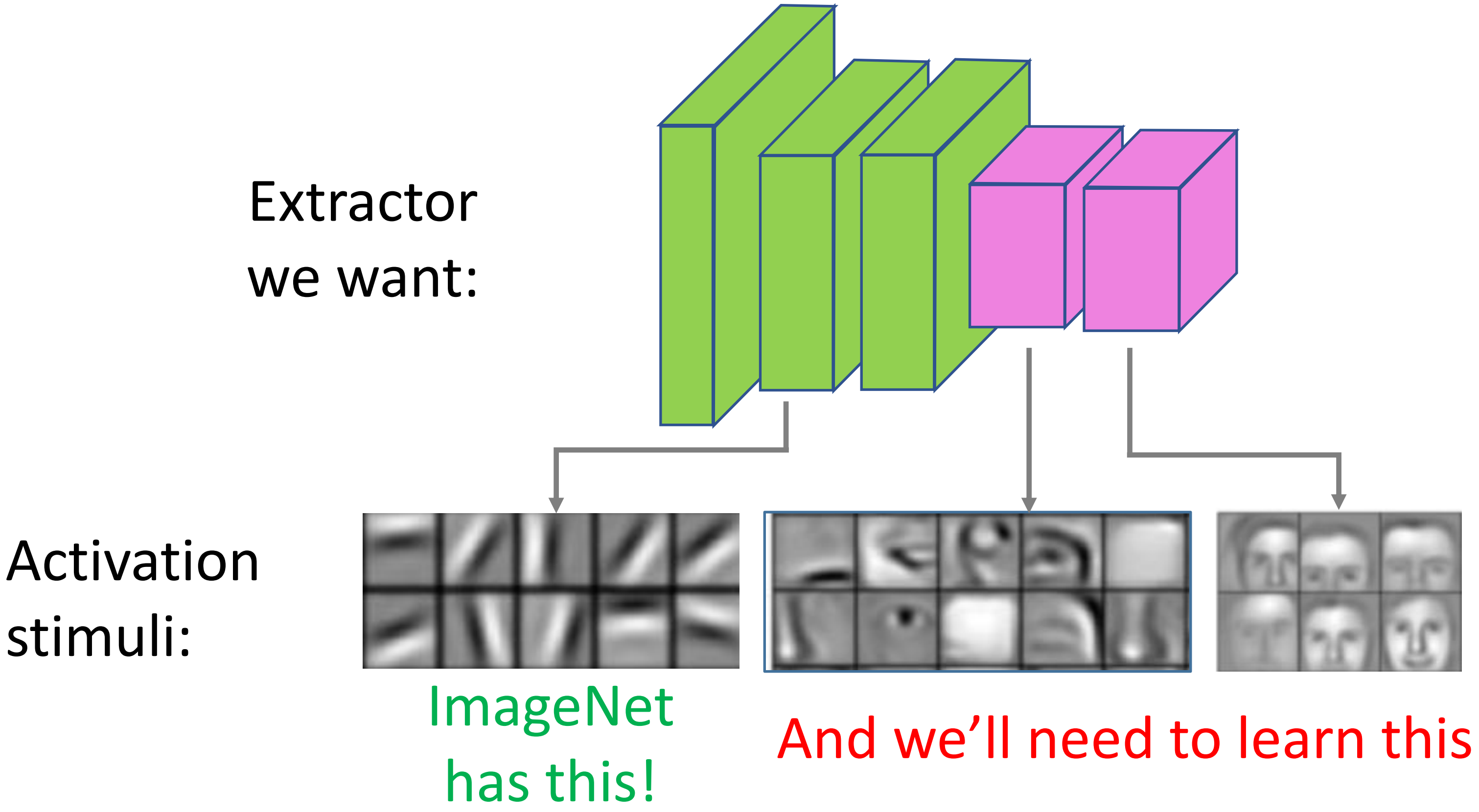

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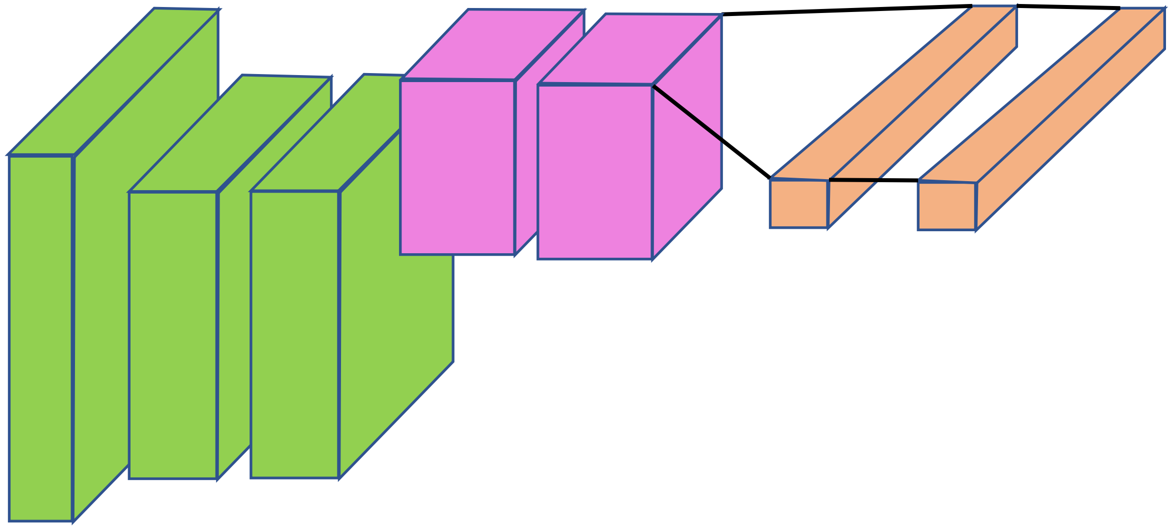
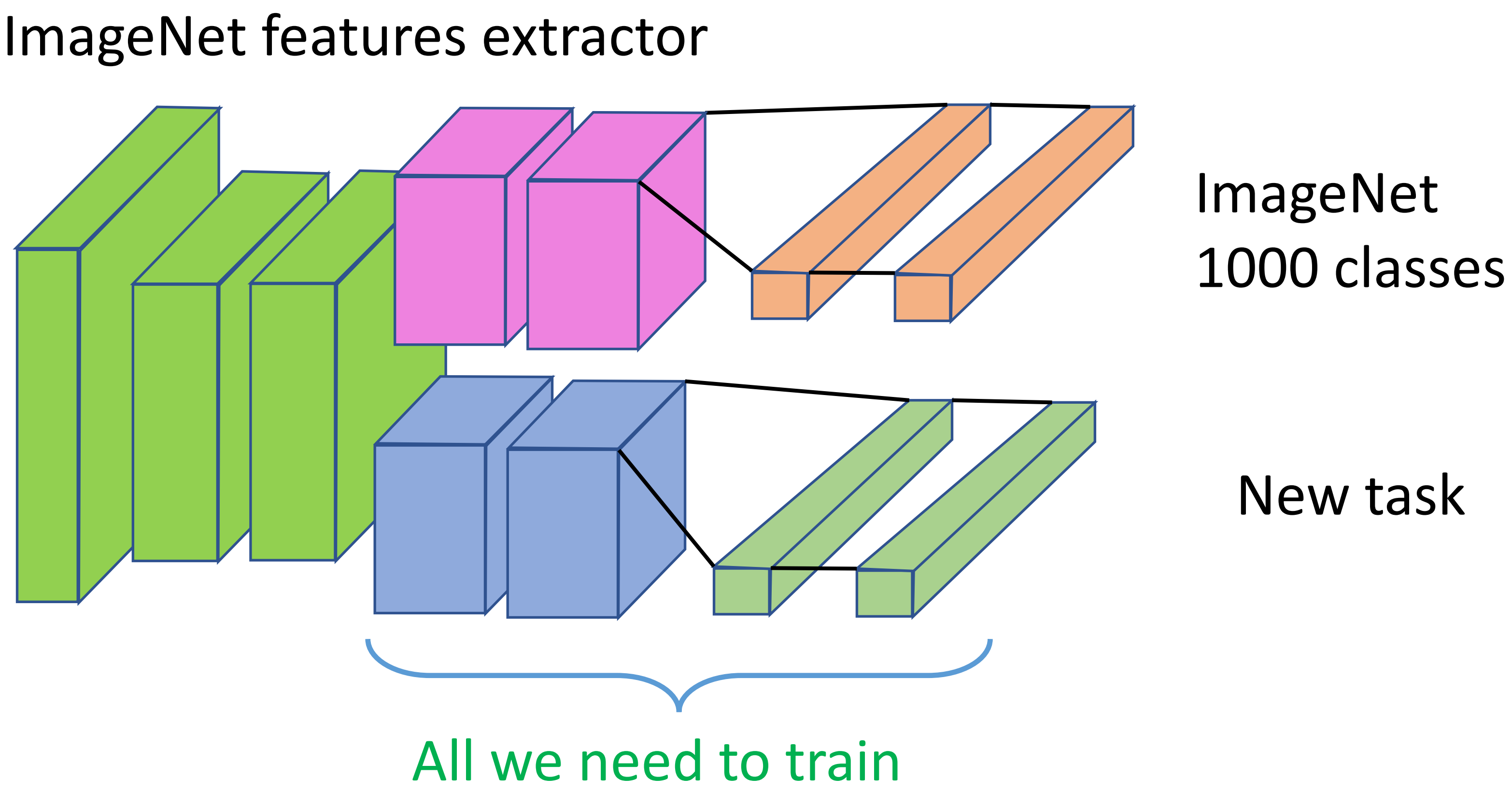
Transfer learning

ImageNet features extractor

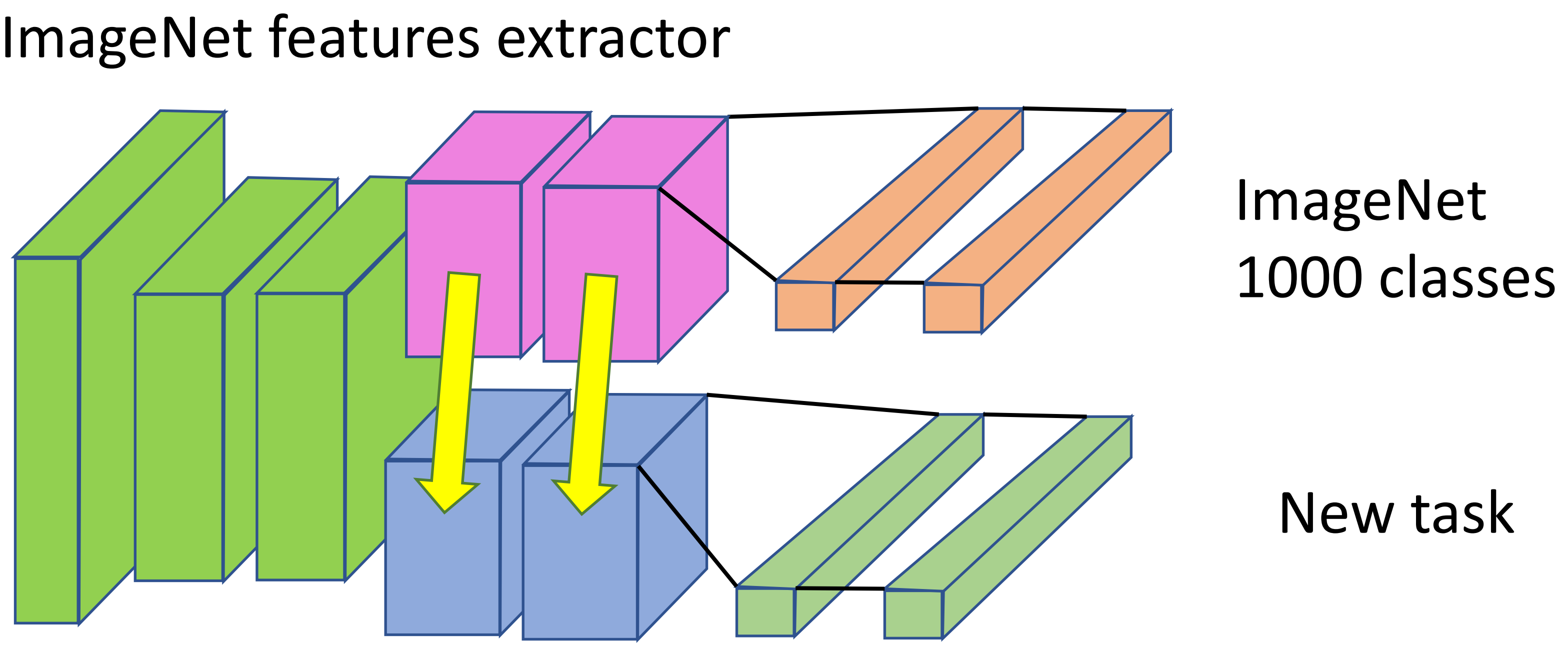


ImageNet
1000 classes

Transfer learning



Fine-tuning



- You can initialize deeper layers with values from ImageNet.
- This is called **fine-tuning**, because you don’t start with a random initialization.
- Propagate all gradients with smaller learning rate.

Fine-tuning

- Very frequently used thanks to wide spectrum of ImageNet classes
- Keras has the weights of pre-trained VGG, Inception, ResNet architectures
- You can fine-tune a bunch of different architectures and make an ensemble out of them!

Takeaways

	ImageNet domain	Not similar to ImageNet
Small dataset	Train last MLP layers	
Big dataset		

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Big dataset	Fine-tuning of deeper layers	Train from scratch

Takeaways

	ImageNet domain	Not similar to ImageNet
Small dataset	Train last MLP layers	Collect more data
Big dataset	Fine-tuning of deeper layers	Train from scratch

Other computer vision tasks

We’ve examined image classification task

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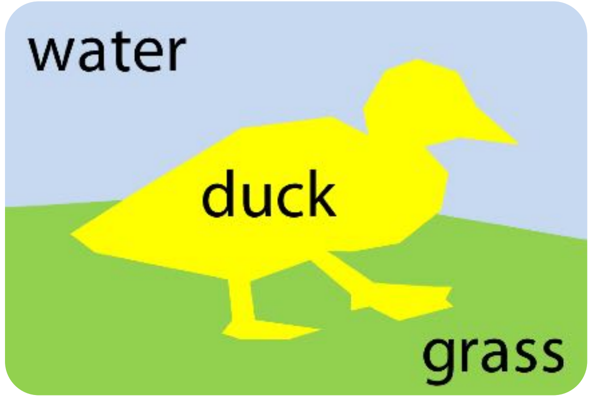
Semantic segmentation:

Other computer vision tasks

We’ve examined image classification task

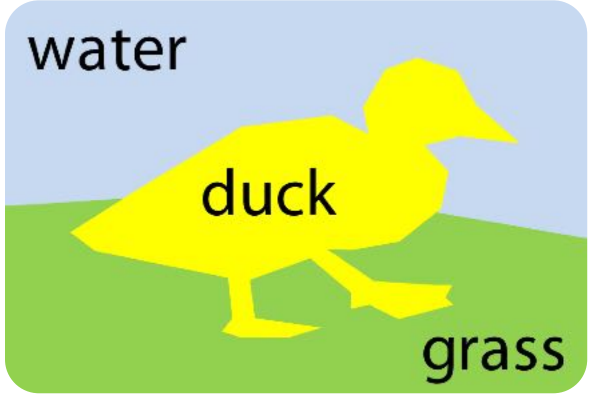
Semantic segmentation:



Other computer vision tasks

We've examined image classification task

Semantic segmentation:



Object classification
+ localization:

Other computer vision tasks

We've examined image classification task

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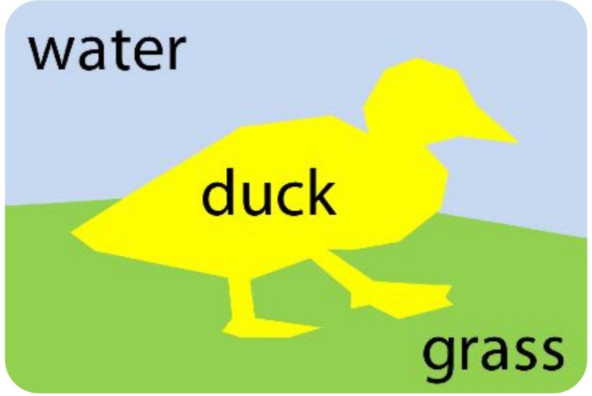

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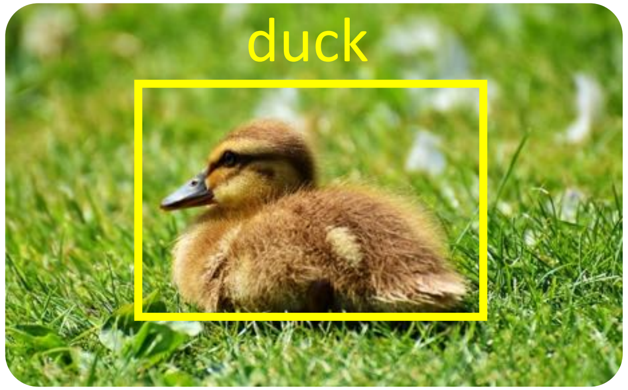

Semantic segmentation

We need to classify each pixel

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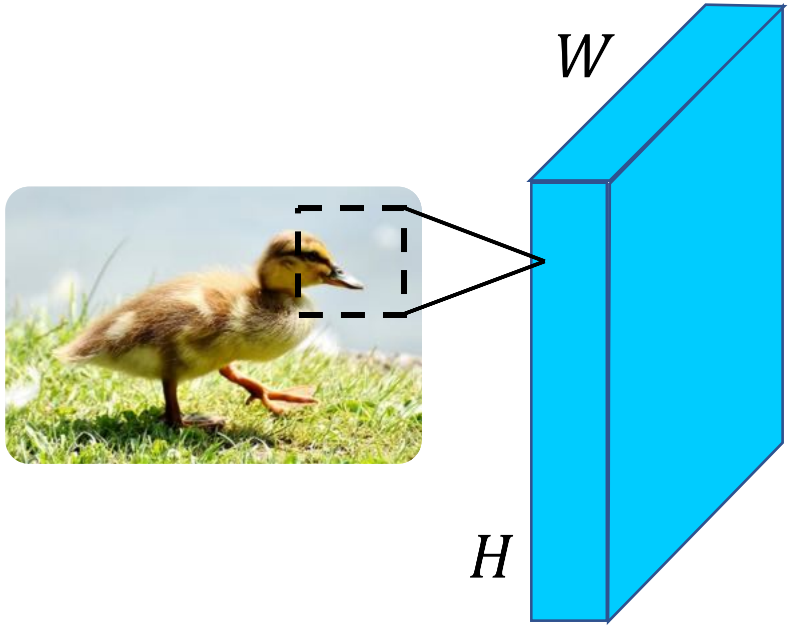

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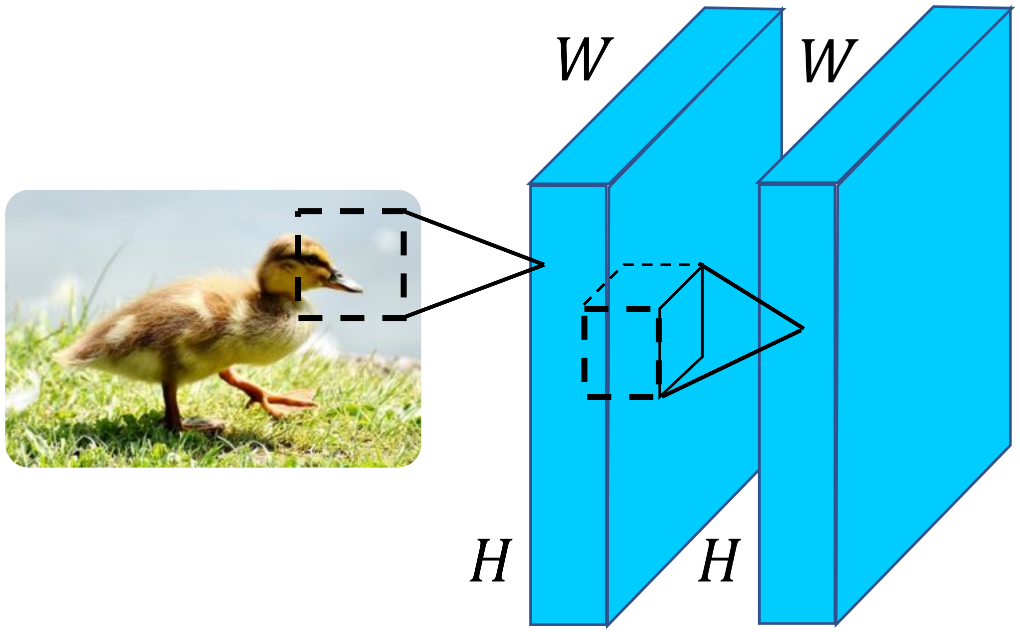

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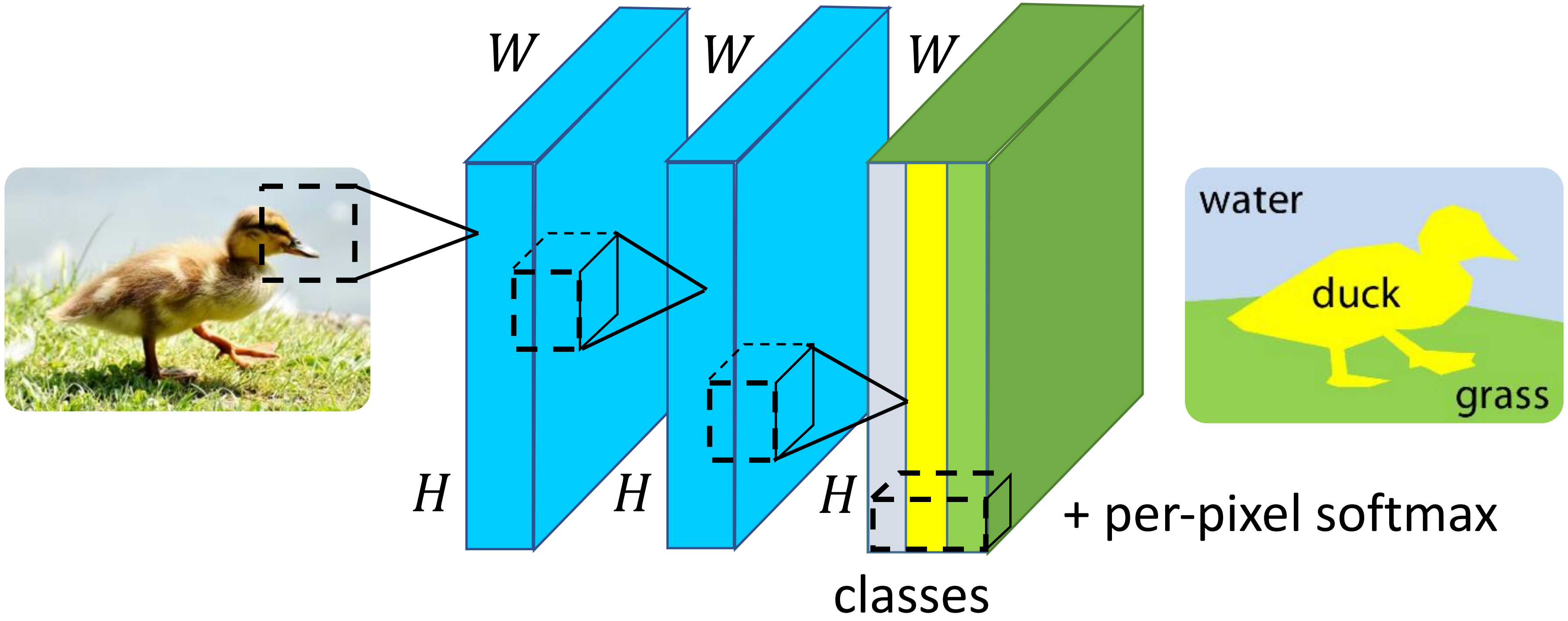

Naïve approach: stack convolutional layers
and add per-pixel softmax

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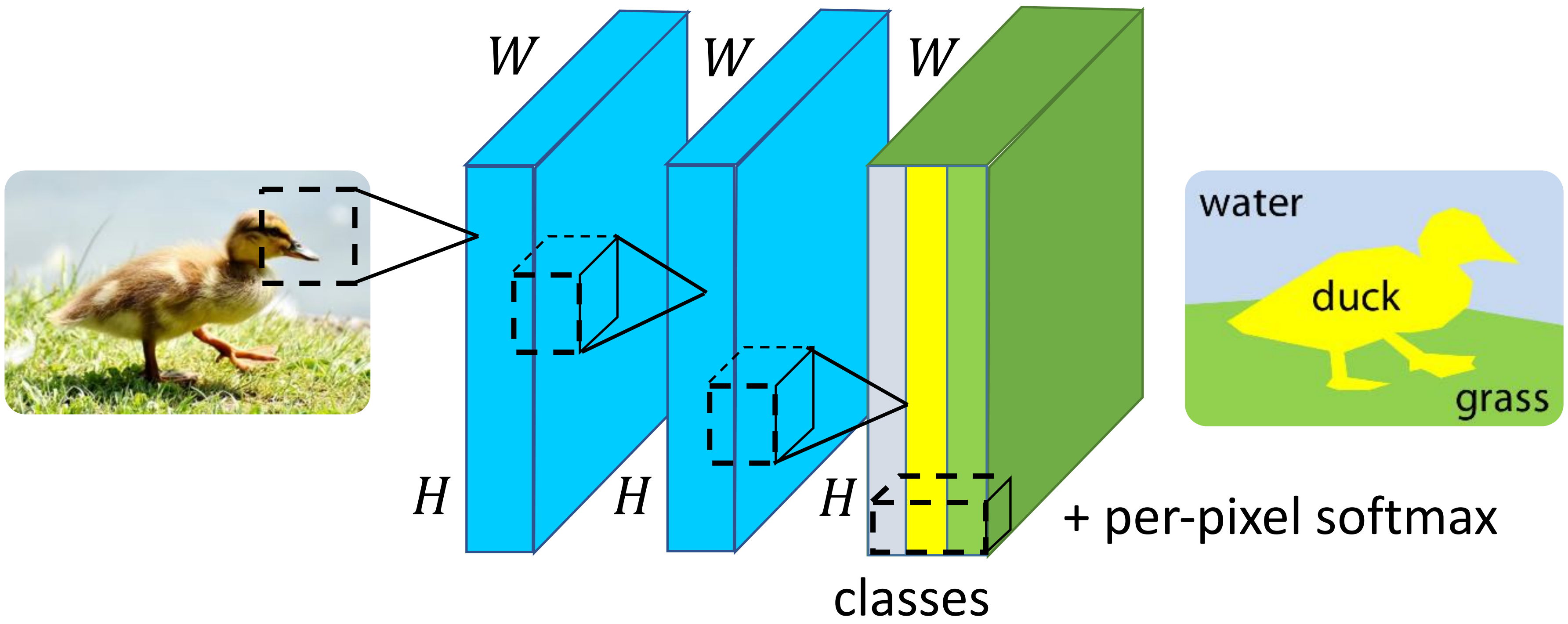

Naïve approach: stack convolutional layers
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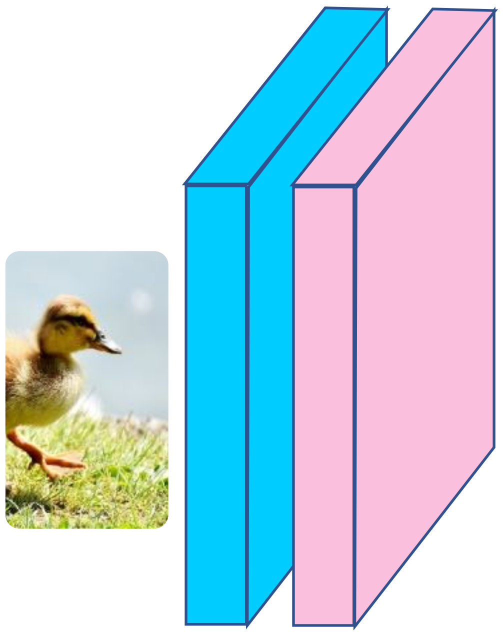
We go deep but don’t add pooling, too expensive

Semantic segmentation

Let's add pooling, which acts like down-sampling



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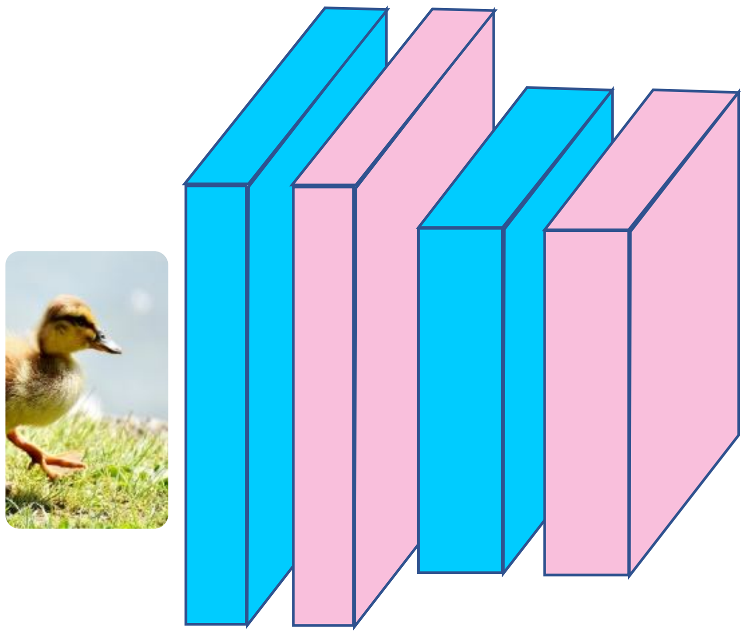

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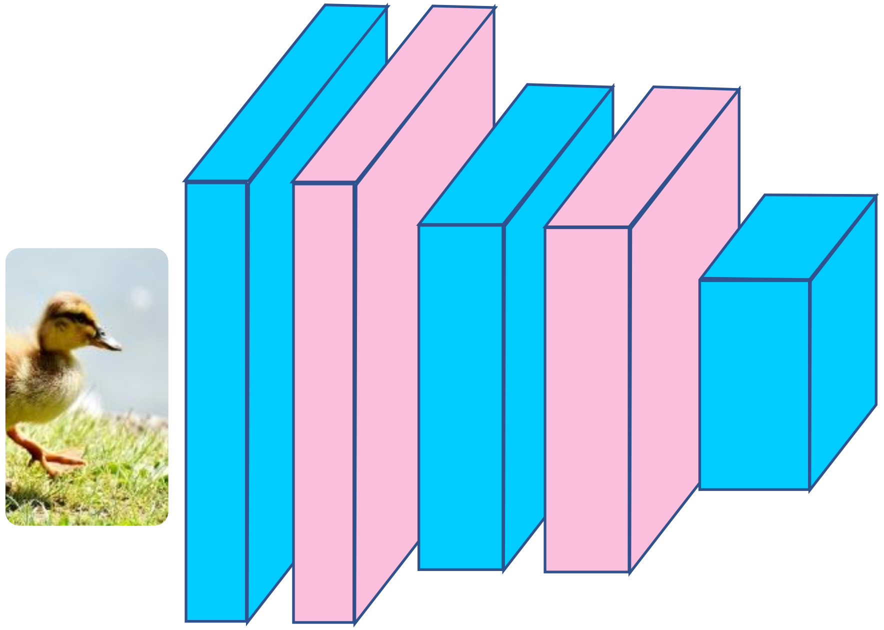

Wait a second!
We need to classify
each pixel!

Need to do **un**pooling!

Semantic segmentation

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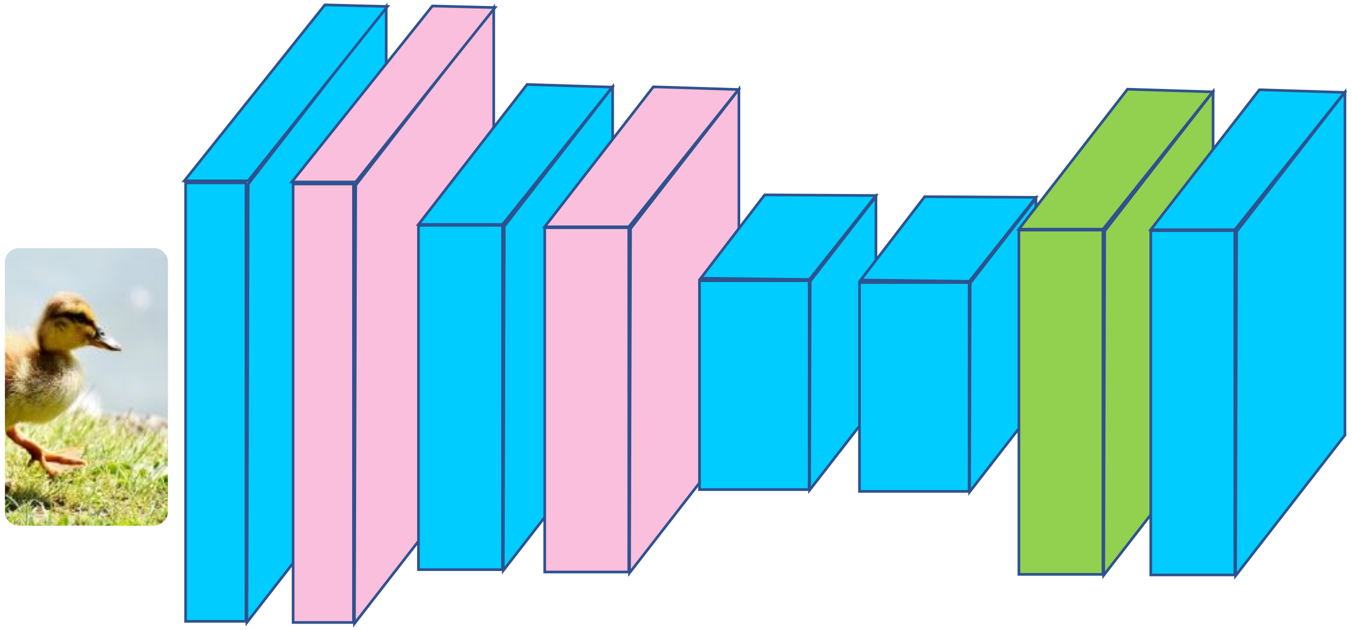

up-sampling

Semantic segmentation

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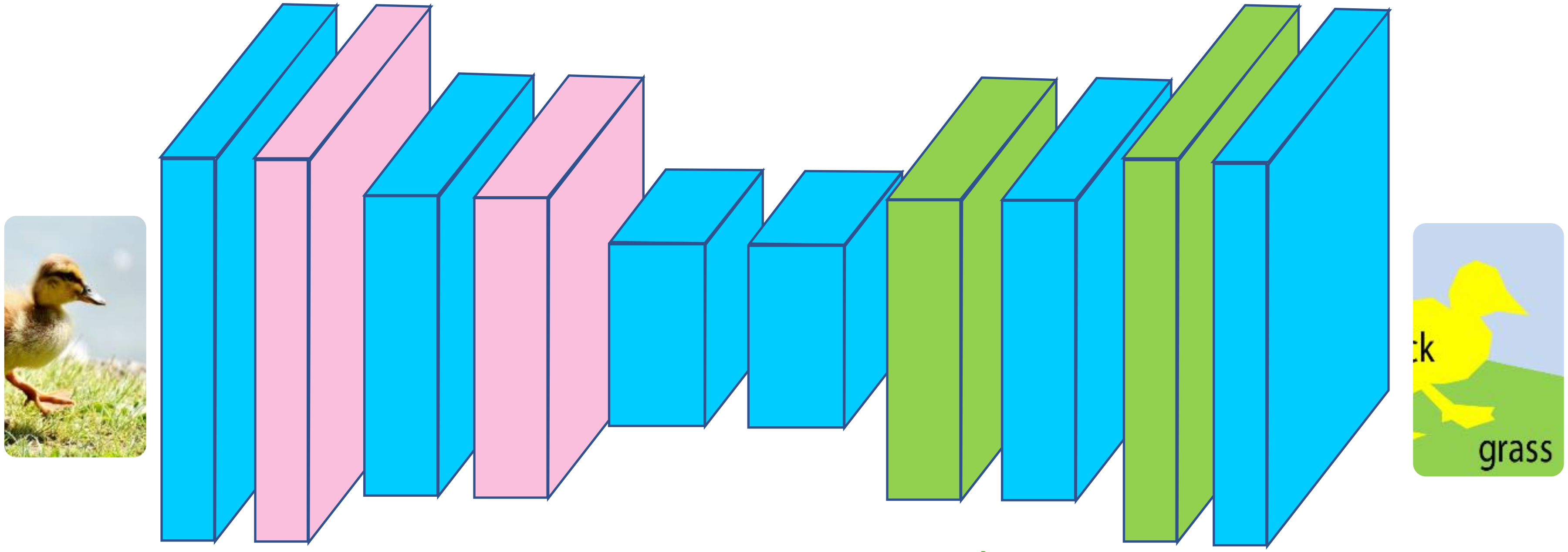
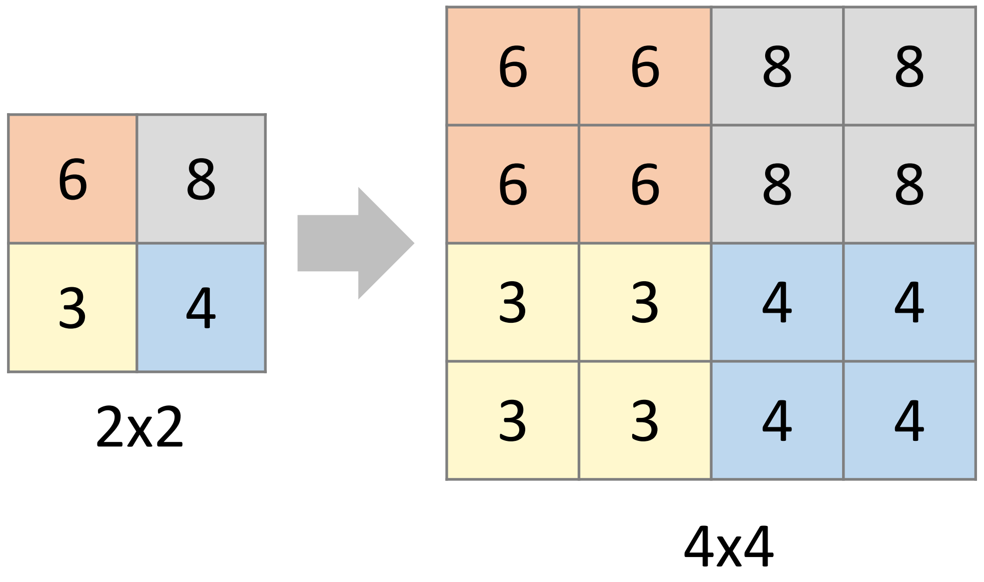


up-sampling

up-sampling

Nearest neighbor unpooling

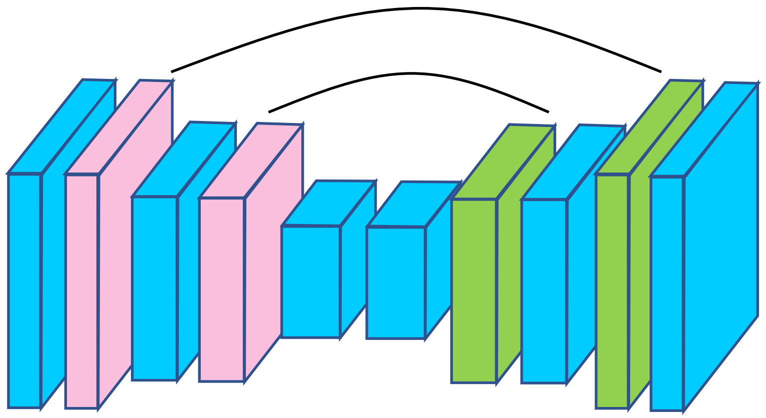
Fill with nearest neighbor values



Pixelated and not crisp!

Max unpooling

Corresponding pairs of downsampling and upsampling layers



Max unpooling

Corresponding pairs of
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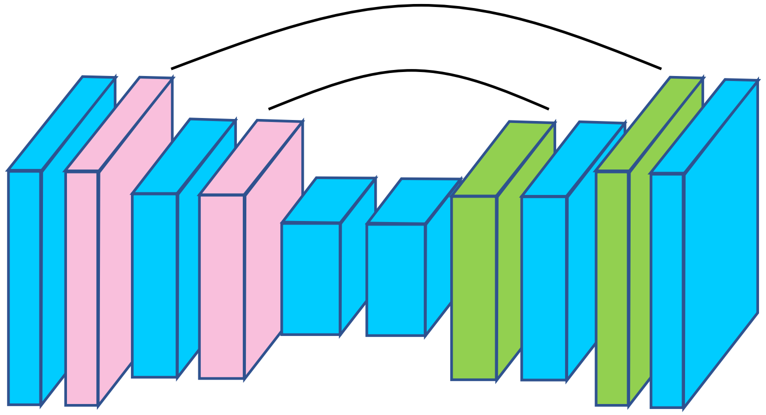

Remember which element was max during pooling, and fill that position during unpooling:

1	2	4	3
2	5	2	0
1	5	2	1
7	3	3	8

4x4

→

5	4
7	8

2x2

→ … →

1	2
3	4

2x2

→

0	0	2	0
0	1	0	0
0	0	0	0
3	0	0	4

4x4

Learnable unpooling

- Previous approaches are not data-driven!
- We can replace max pooling layer with convolutional layer that has a bigger stride!
- What if we can apply convolutions to do unpooling?

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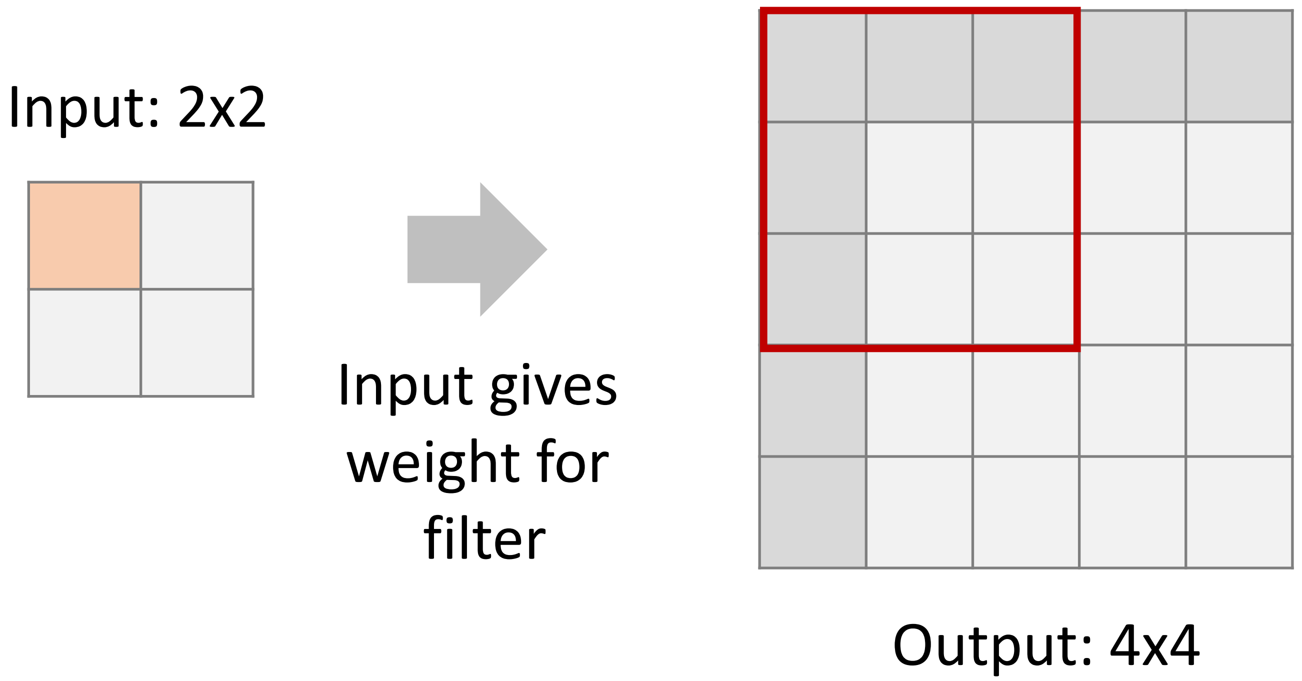

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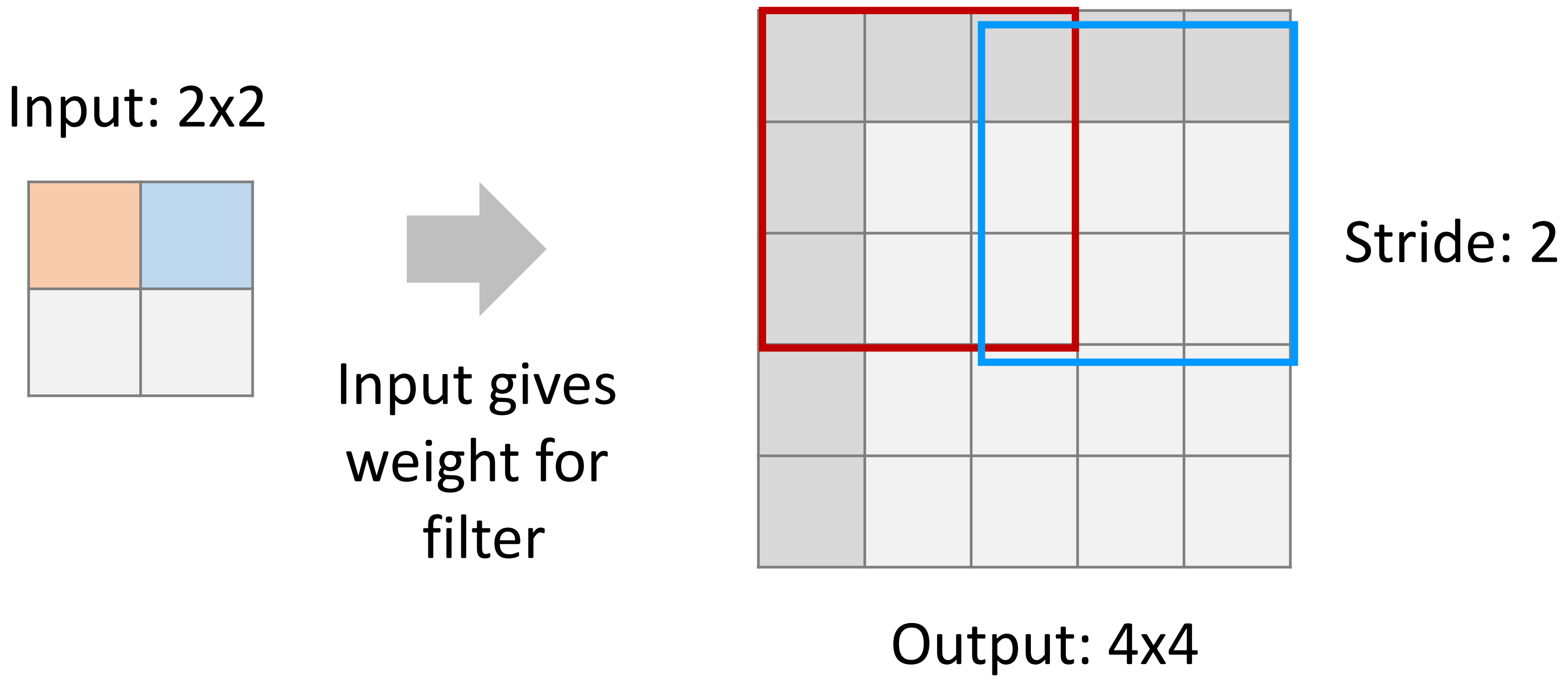

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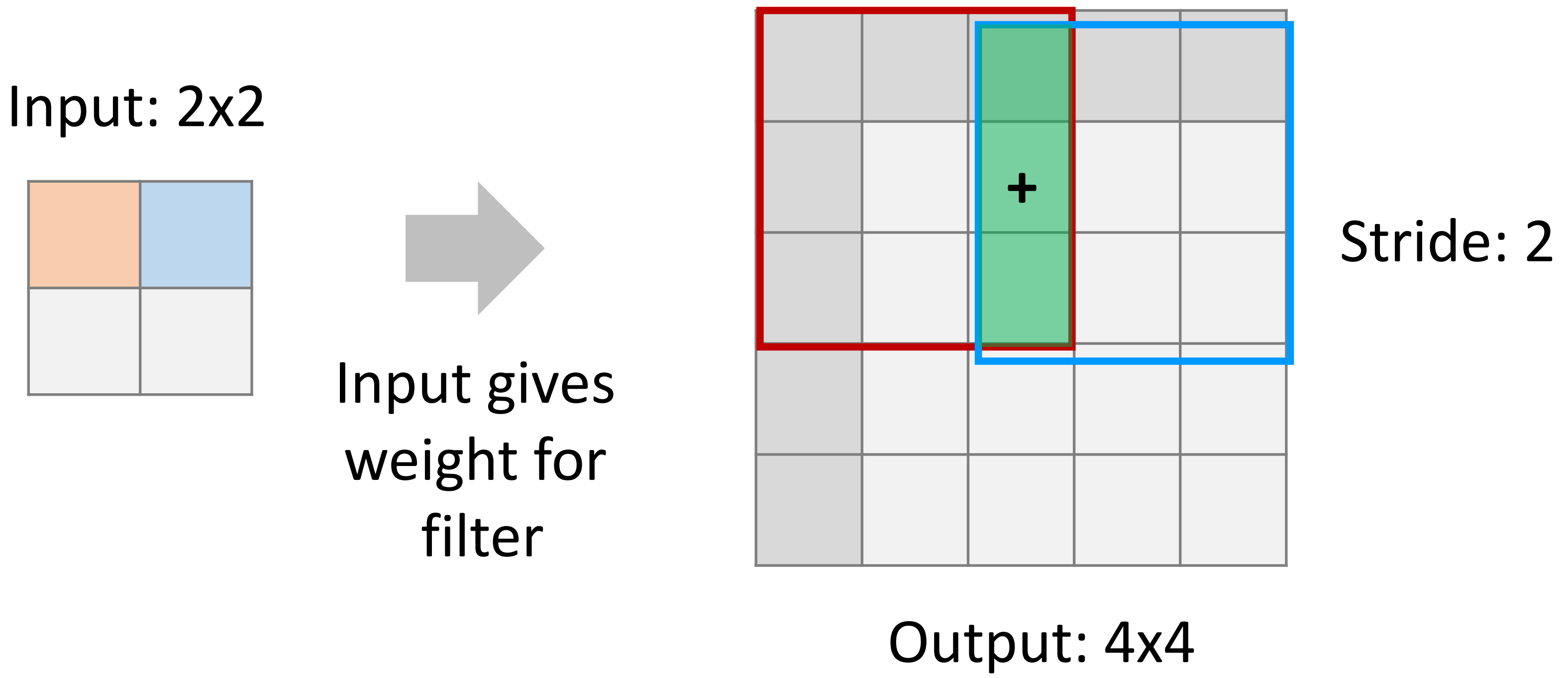
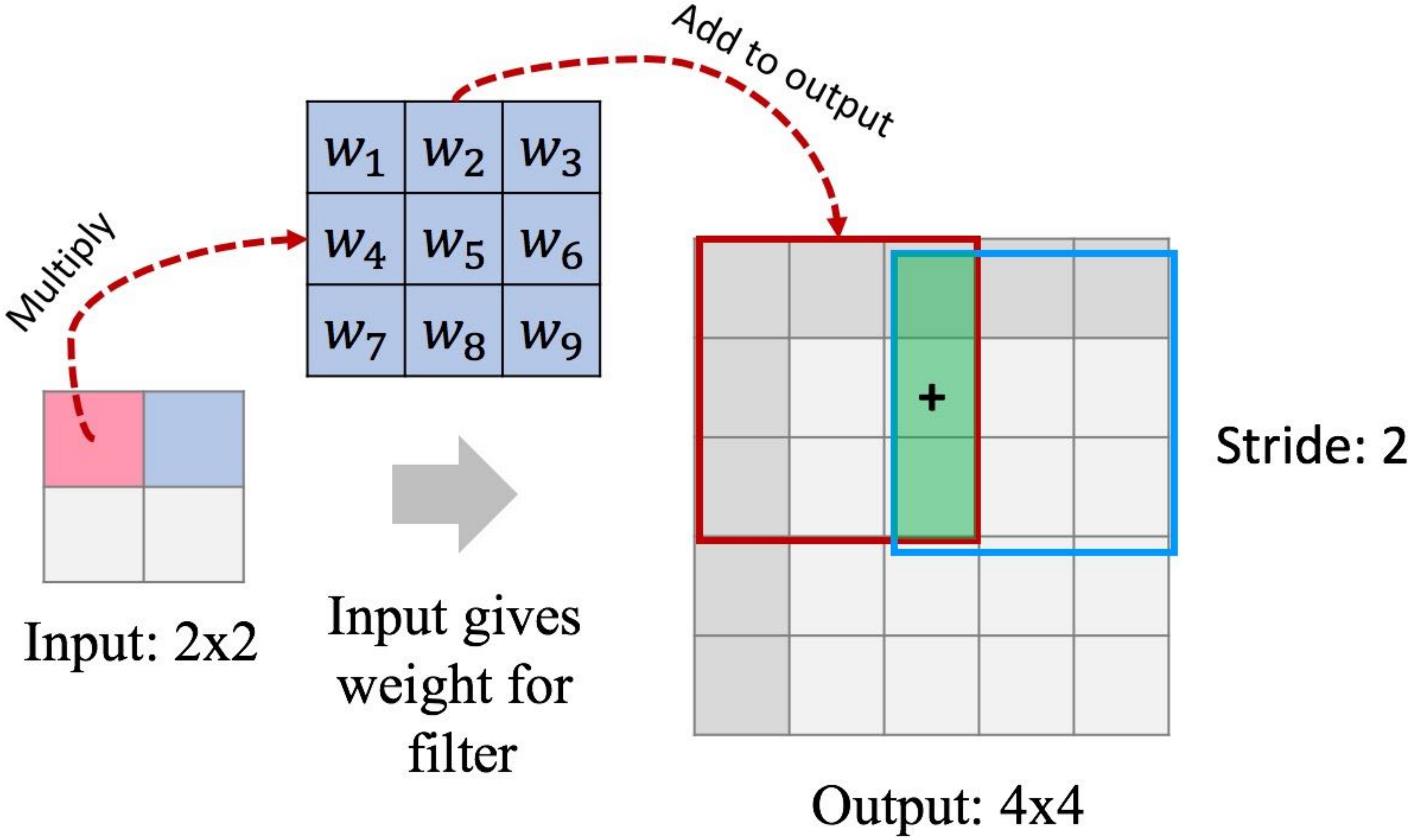
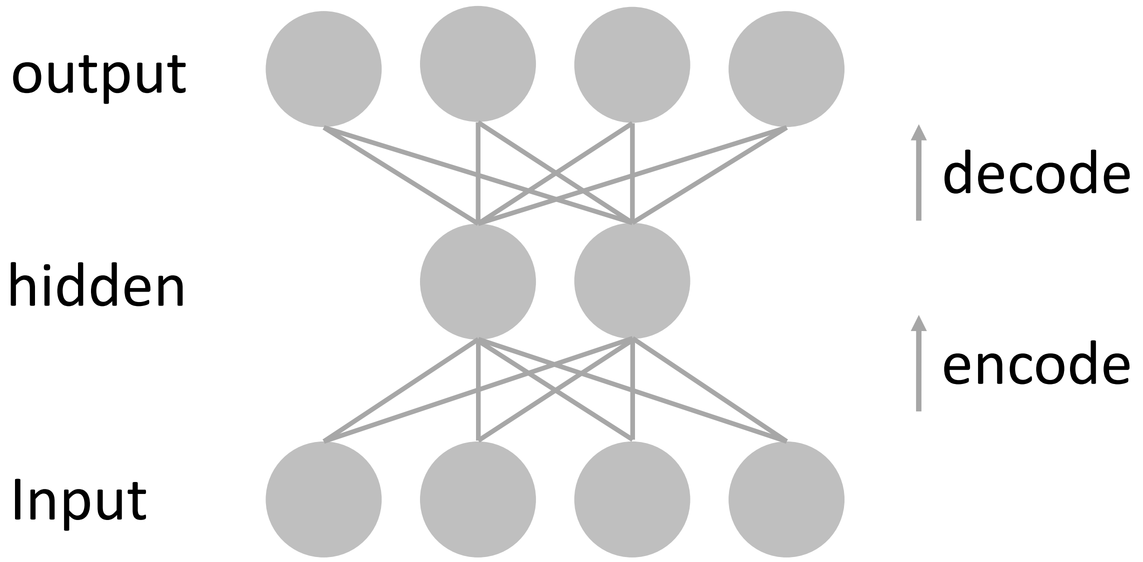


Transpose convolution



Autoencoders

- Encoder = data to hidden
- Decoder = hidden to data
- Decoder(Encoder(x)) ~ x



Linear case: “similar” to PCA or SVD

Example: matrix factorization

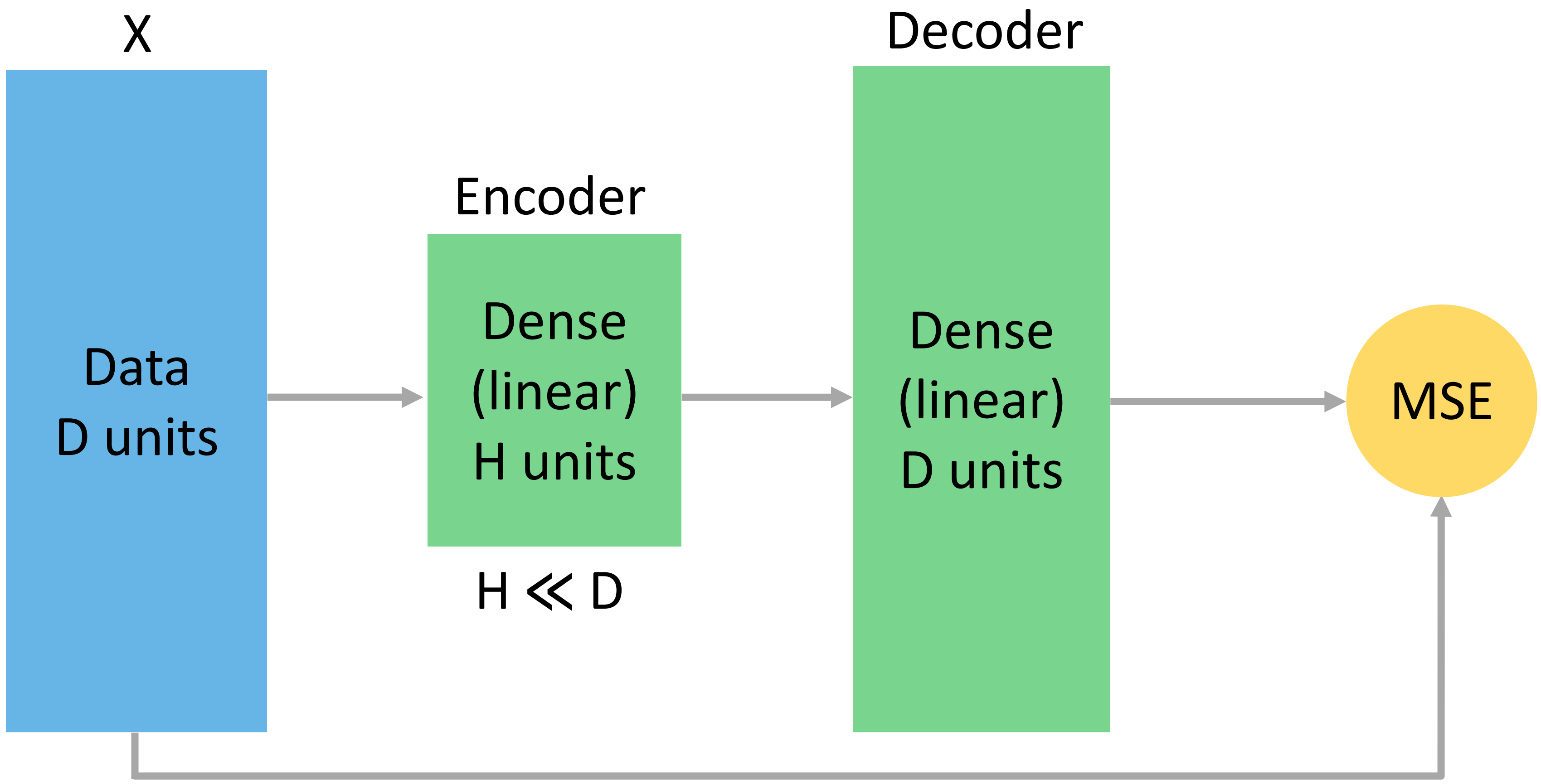
$$X = U \times V^T$$

Minimizing reconstruction error

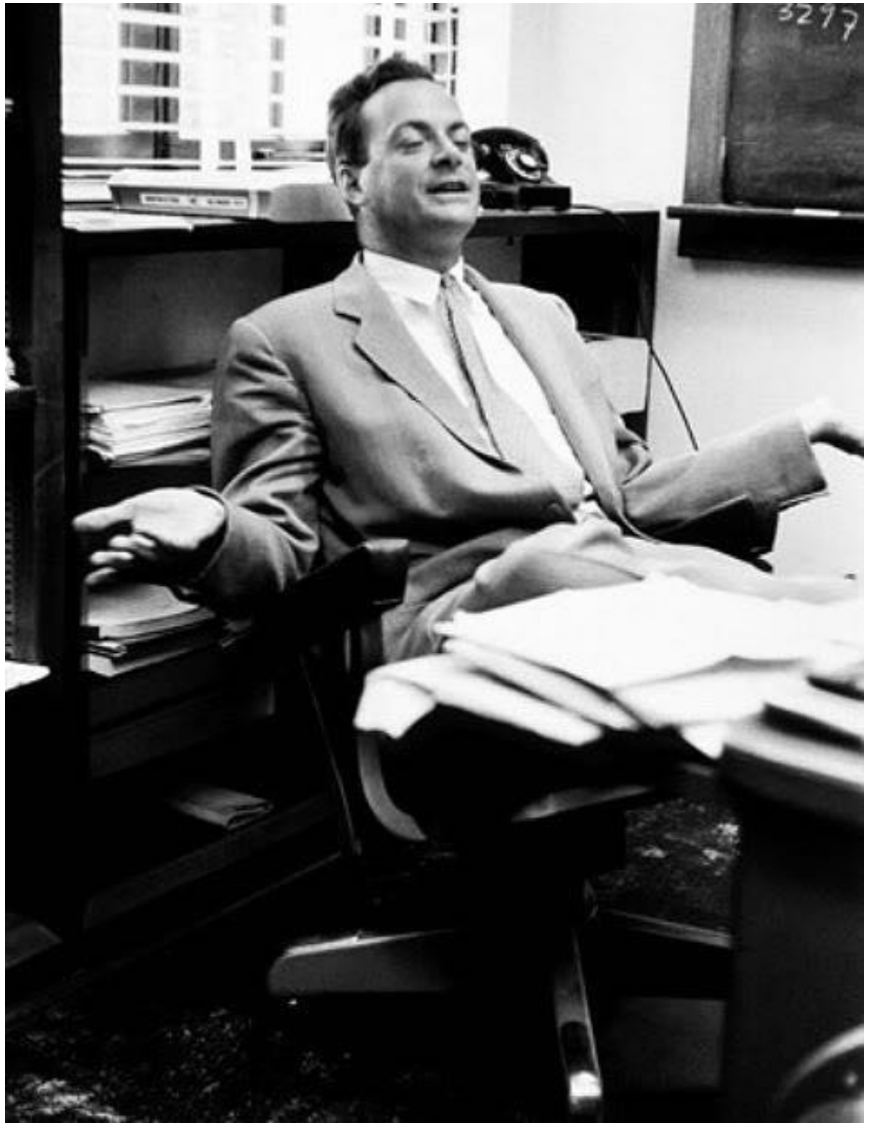
$$\|X - U \cdot V^T\| \to \min_{U,V}$$

Matrix decompositions

Как нейросеть

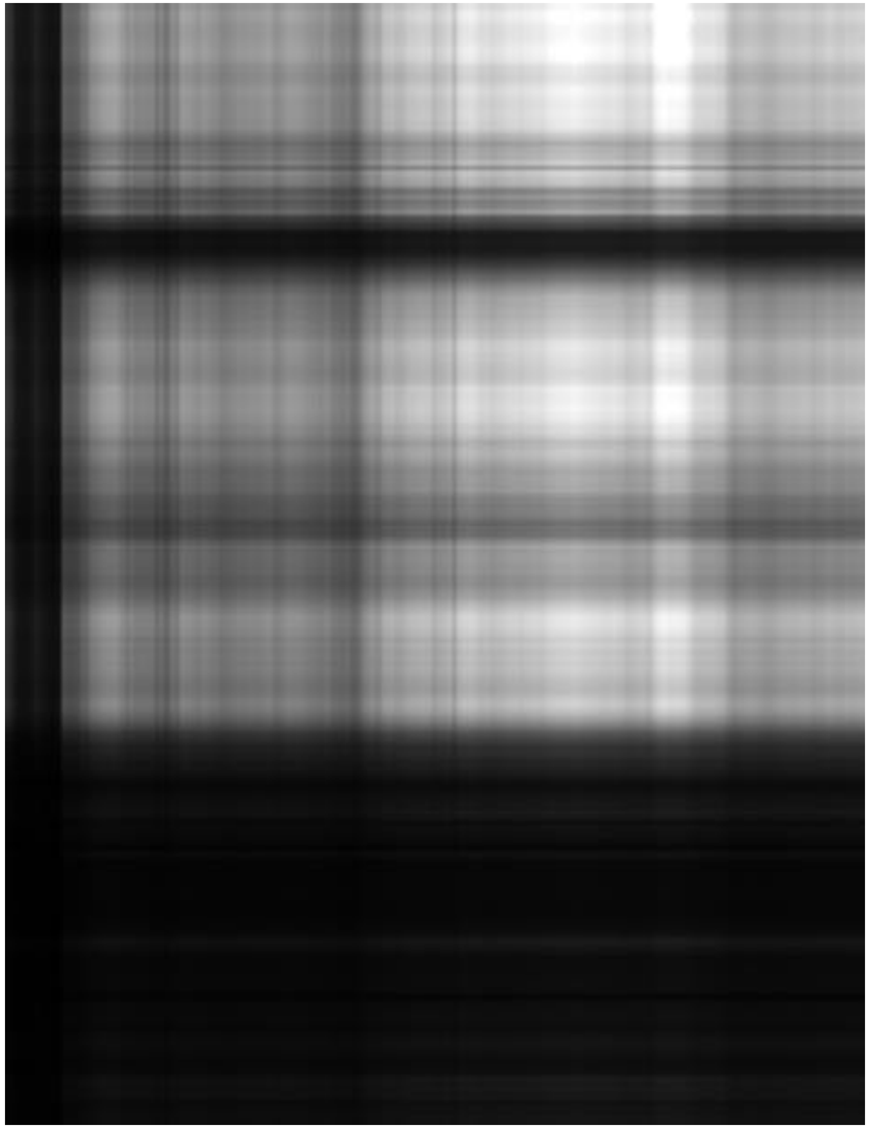


Интерпретация



Исходная картинка, попробуем применить SVD

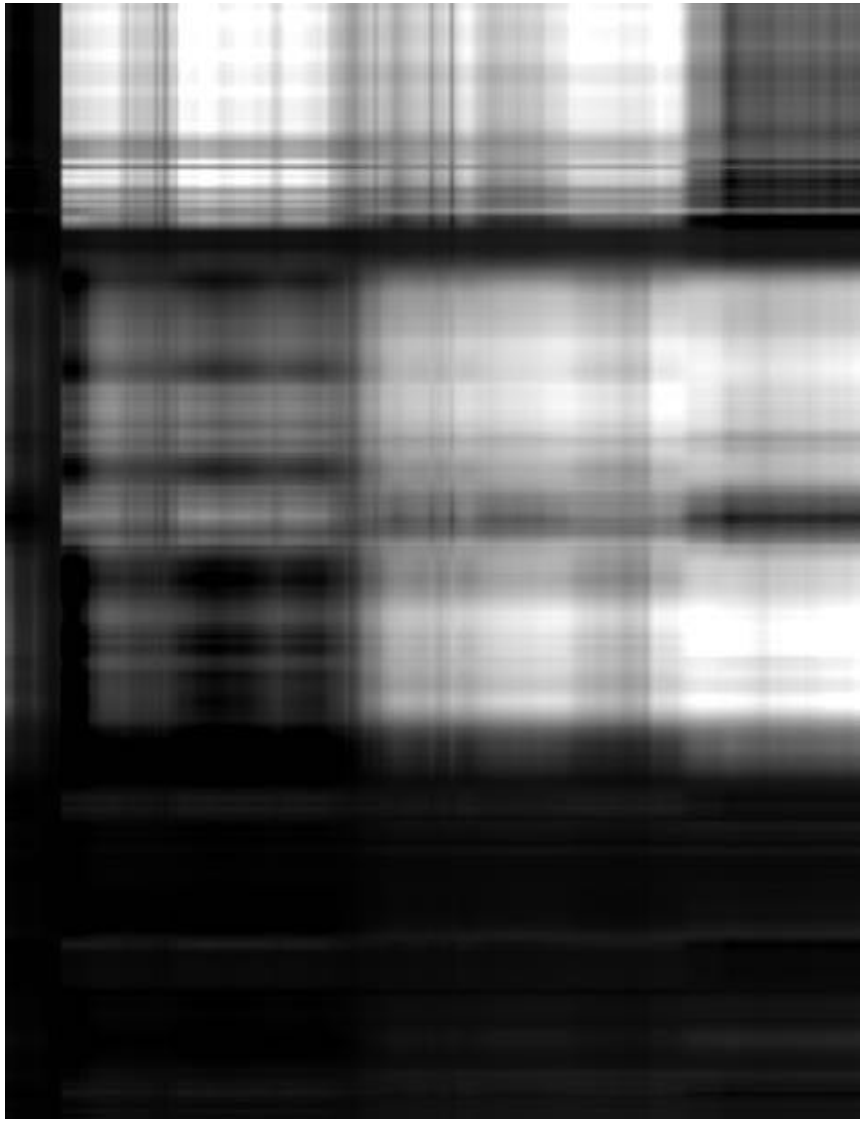
Интерпретация



Применили SVD и взяли только первый главный фактор.

k = 1

Интерпретация



Взяли 2 главных фактора.

$k = 2$

Интерпретация

k = 10

Интерпретация

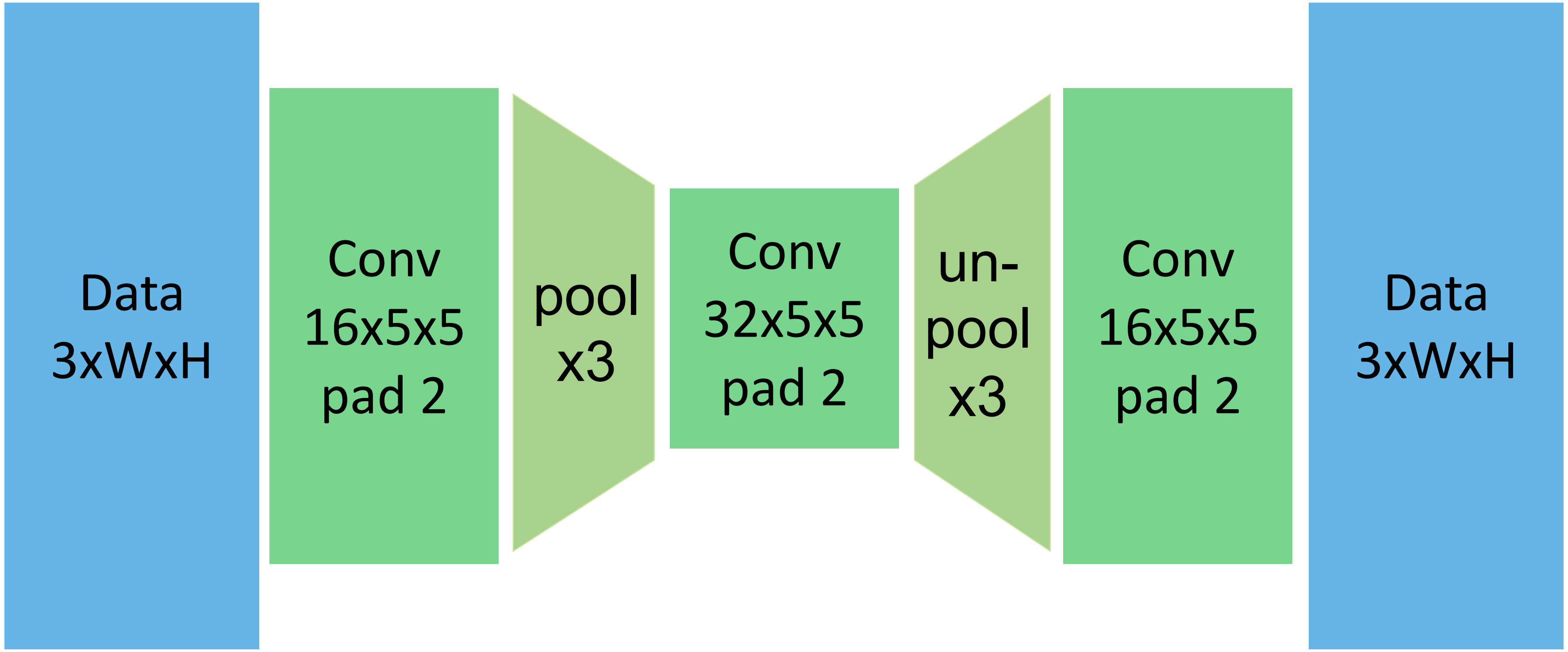
k = 50

Довольно неплохо!

Исходный размер был: 475x620.

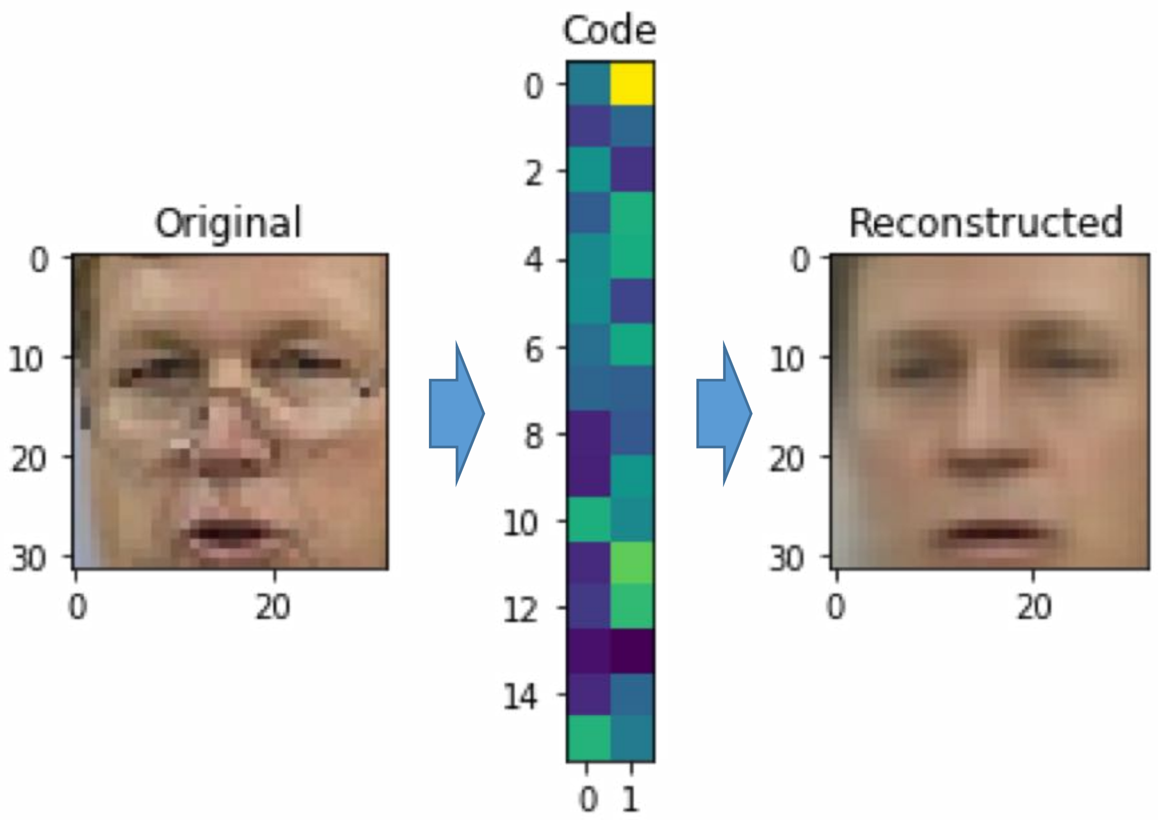
Что дальше?

Нужно учить глубокое преобразование!



Working with neural representations

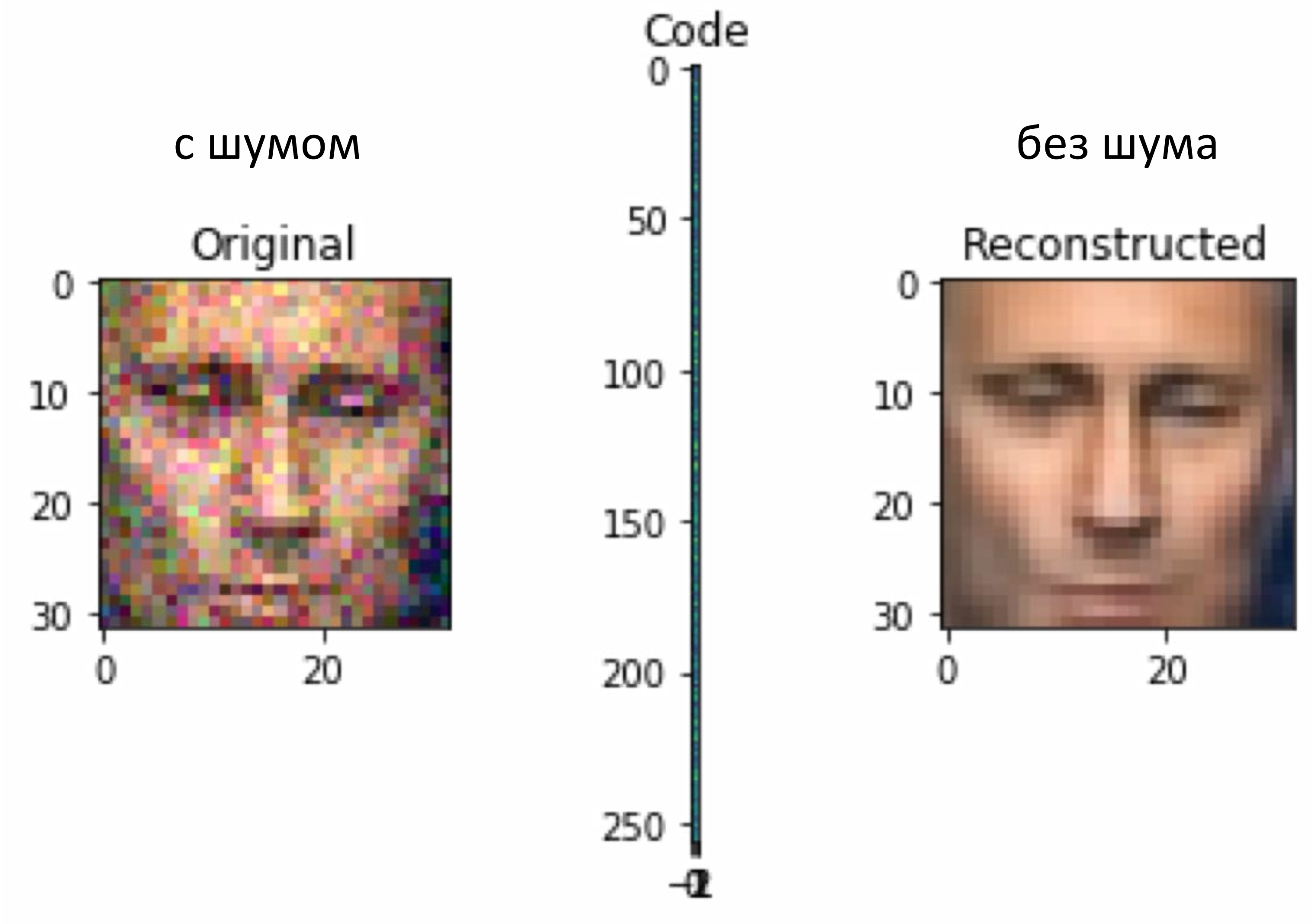
- We need to understand that a NN can convert an object to a small dense vector, which encodes the semantics:



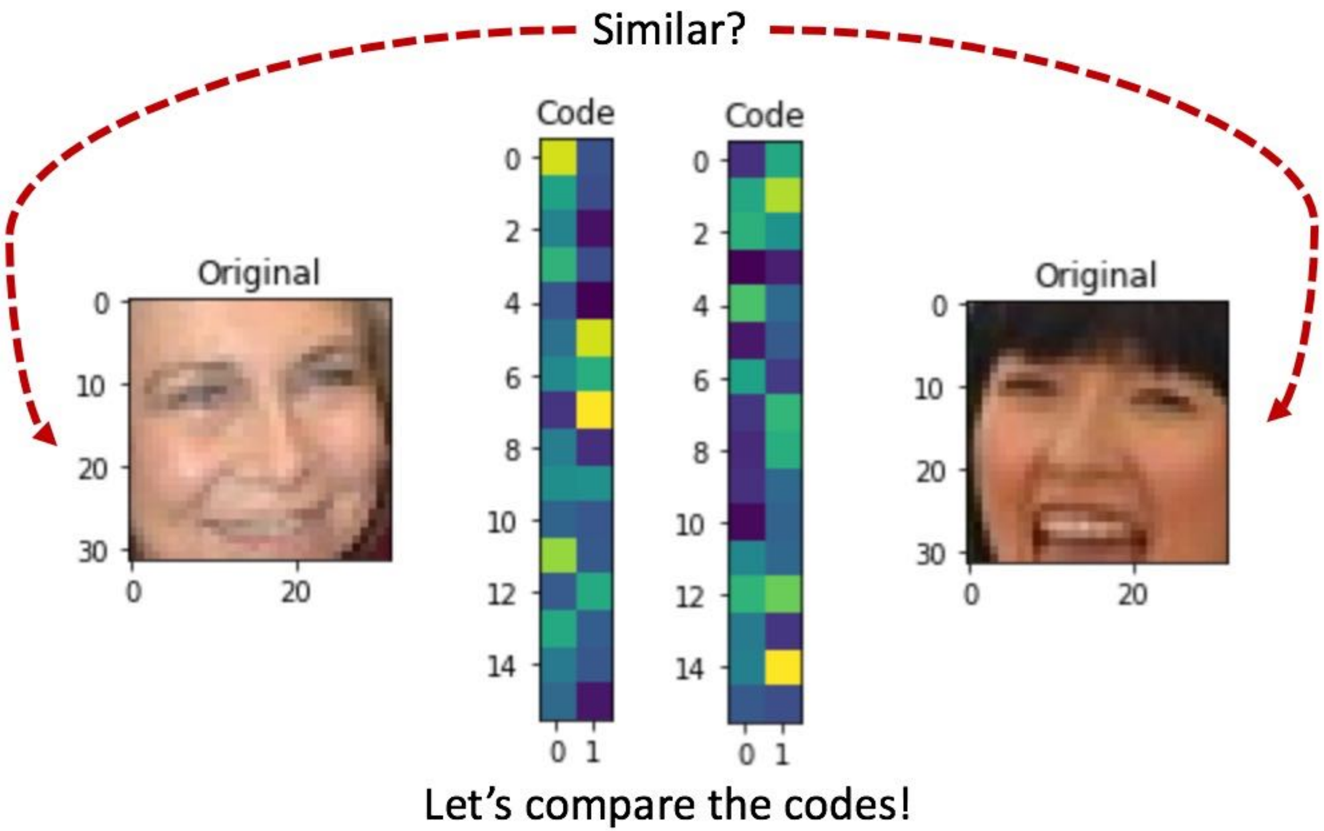
Denoising autoencoders

с шумом

без шума



Поиск похожих картинок



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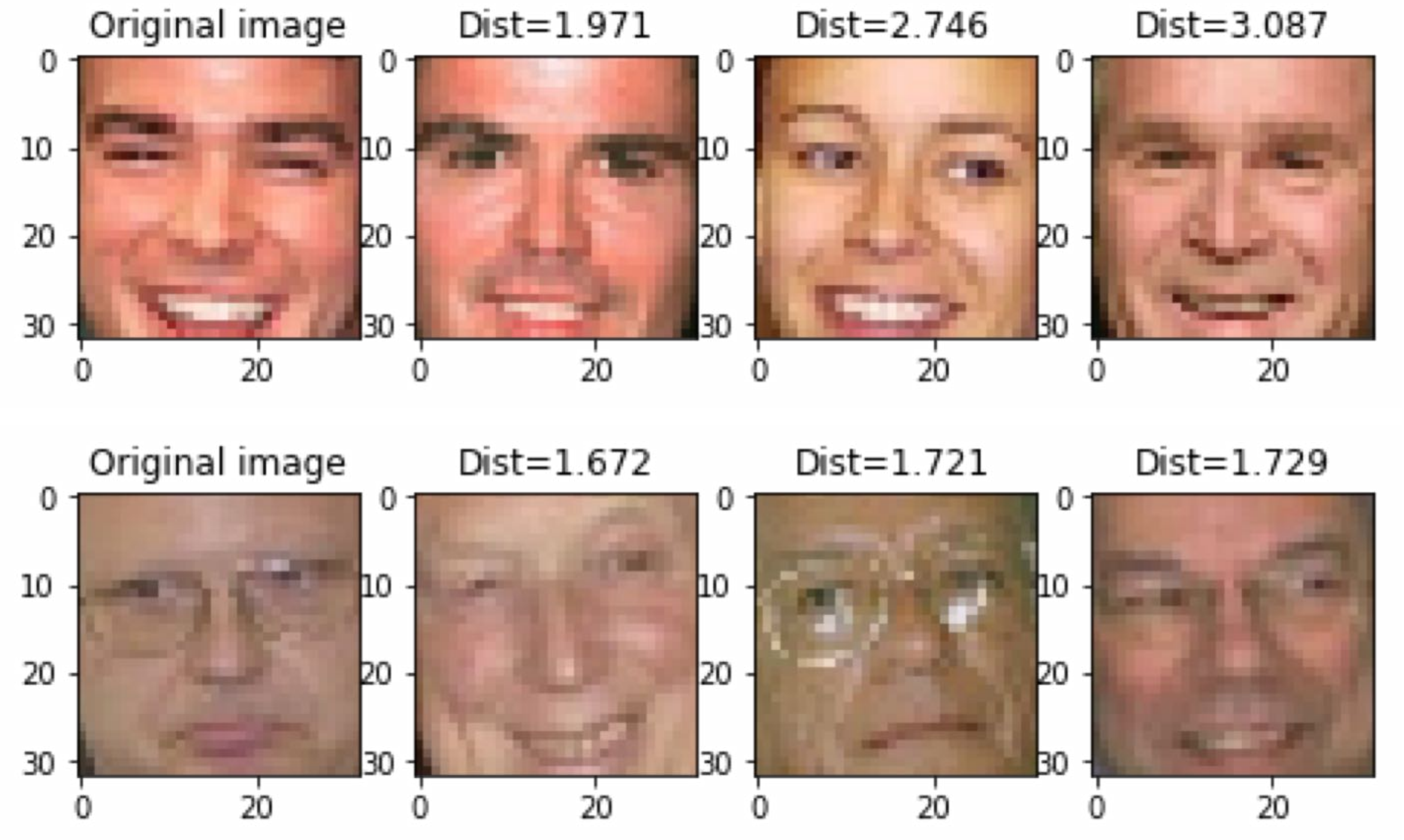
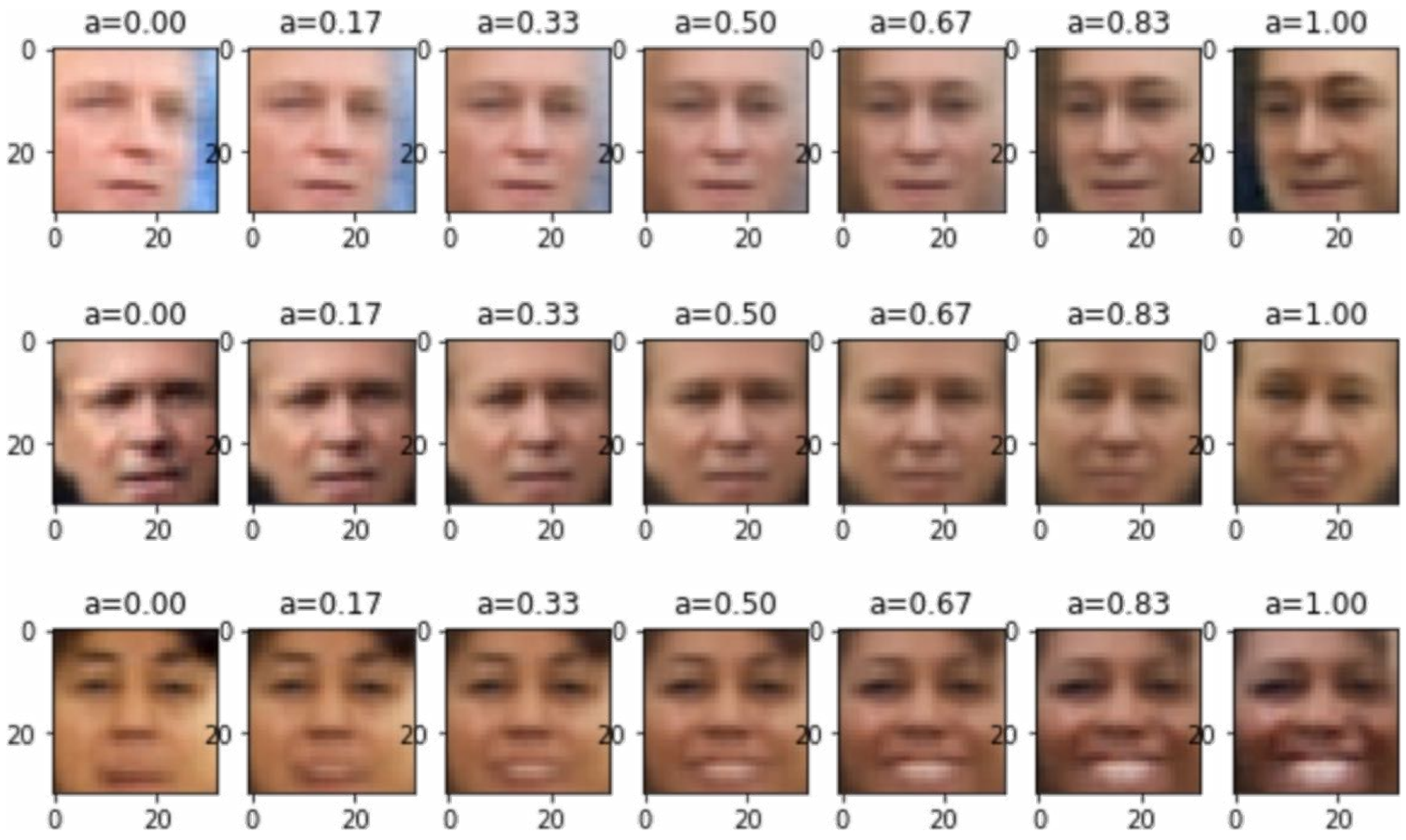


Working with neural representations

- You can play around with those vectors to morph images:

А

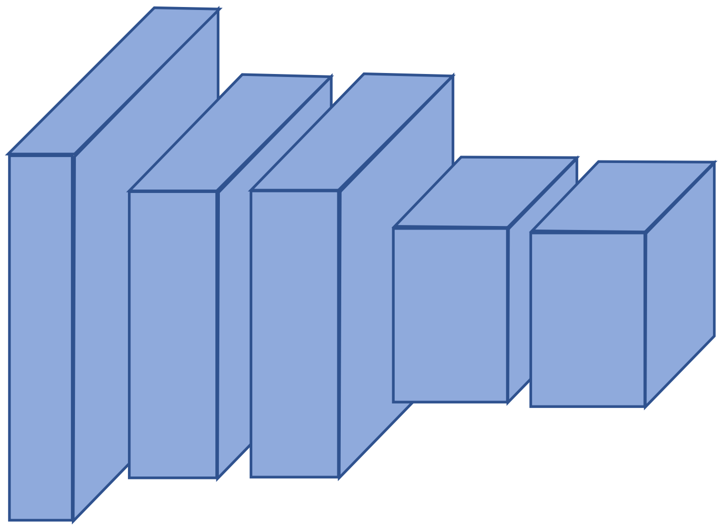


Б

Путешествуя в пространстве имбедингов плавно меняется картинка

И самое классное!

- Нам не нужны размеченные данные!
- Учим экстрактор фичей забесплатно!



Ссылки

- https://blog.keras.io/building-powerful-image-classification-models-using-very-little-data.html
- https://github.com/hse-aml/intro-to-dl/blob/master/week4/Autoencoders-task.ipynb