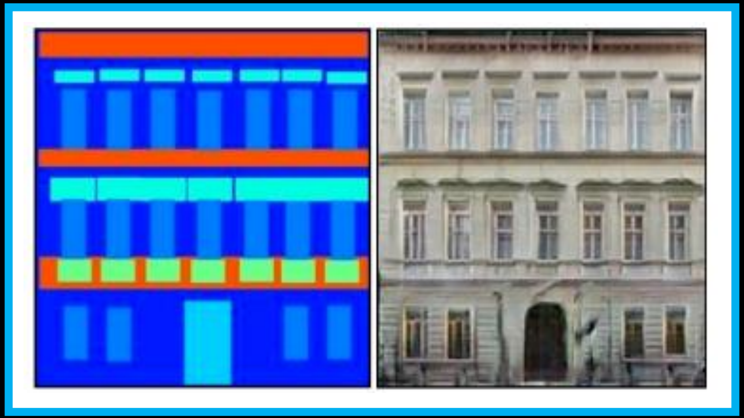
Exploring Machine Intelligence

Week 6, Generative Models II

~ Vítek Růžička

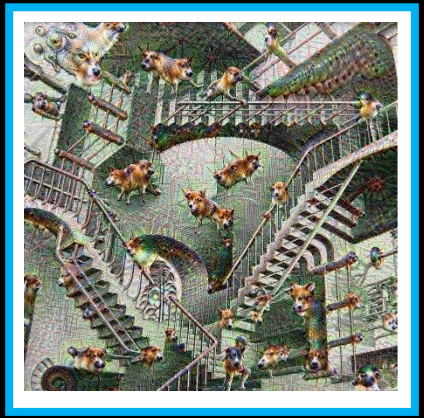
Motivation for today

Overview of additional machine learning techniques:



pix2pix

style transfer



deep dream

Today

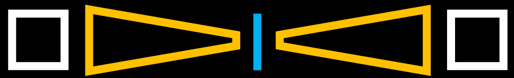
Overview of some additional Generative Models:

- **Pix2pix** and domain to domain transfer
- **Style transfer** technique
- **Deep Dream** technique

Larger focus on the practical session:

- Using **Progressively Growing GAN** – detailed instructions from data processing to model training

Domain to Domain

- We have seen few models working with images on outputs and inputs (for example AutoEncoders). Similar architectures can be also used to model **relation between two domains** of data. 

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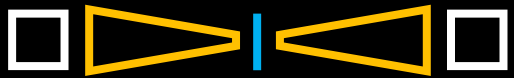
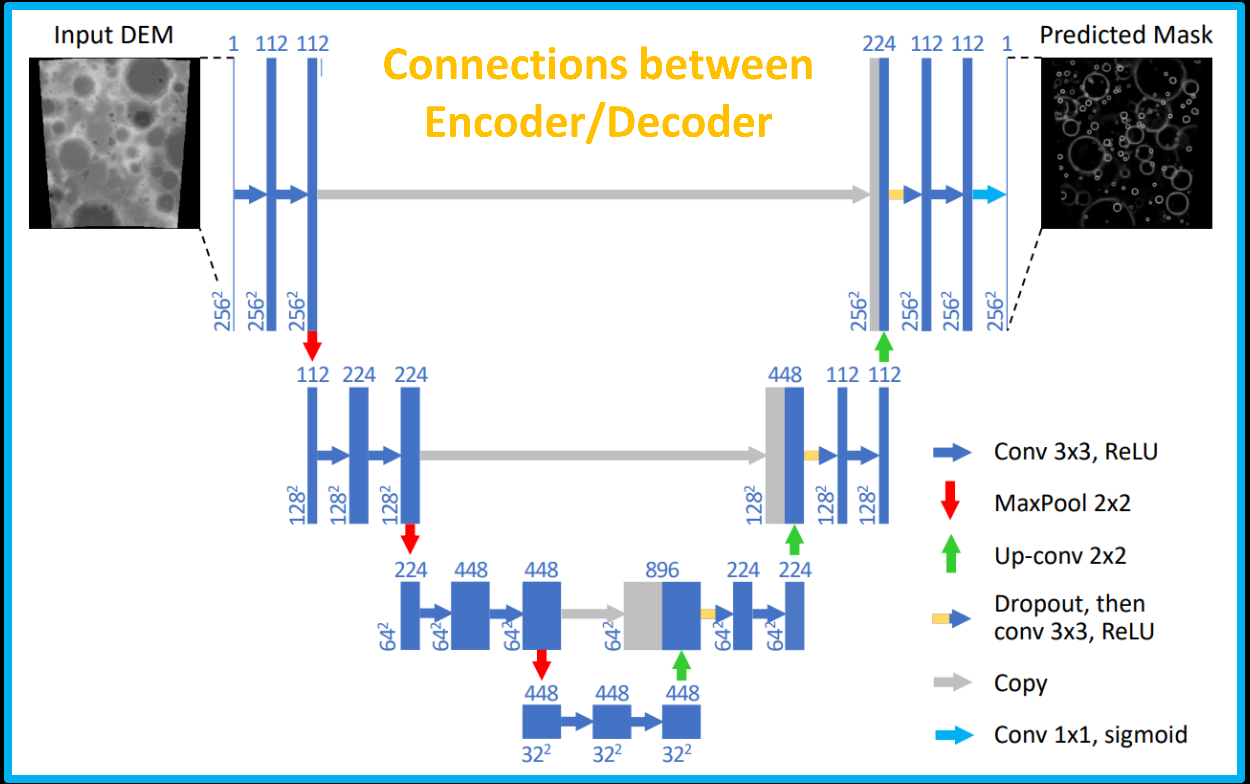
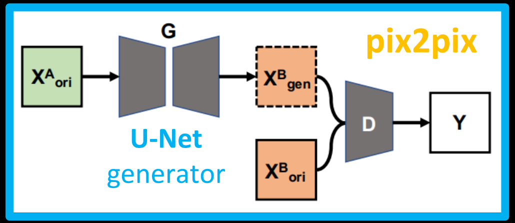
- We have seen few models working with images on outputs and inputs (for example AutoEncoders). Similar architectures can be also used to model **relation between two domains** of data. 

- Let's look at a predecessor of this idea, the **U-Net model**:
  - Paper with U-Net applied on the task of lunar crater identification

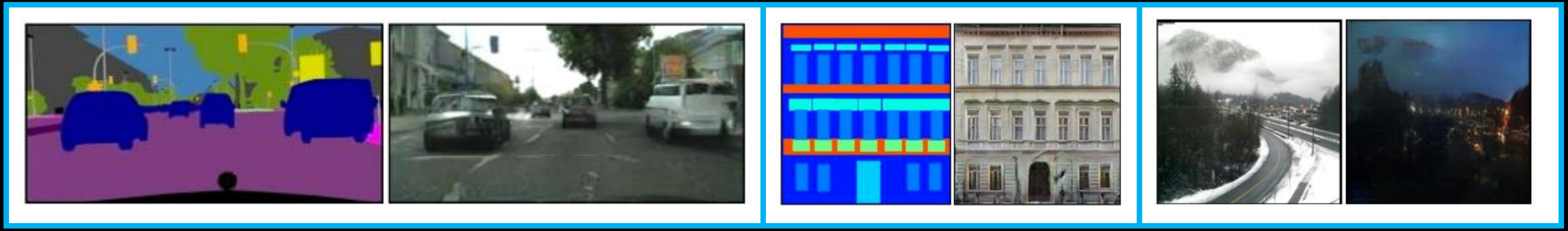


(PS: U-Net is from 2015, this [paper](#) from 2018)

Pix2Pix

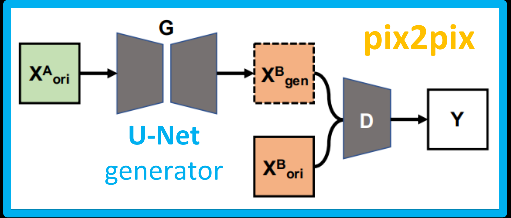


- General purpose **image-to-image translation:**
  - From their paper: *"Many problems in image processing, computer graphics, and computer vision can be posed as "translating" an input image into a corresponding output image."*
  - Translating without specifically defining the rules – data-driven translating between two domains by showing **paired** examples:
    - [Image from A, Corresponding Image from B] * N samples



(PS: there is also an un-paired version called CycleGAN = images from two domains, but they don't have to correspond)

Pix2Pix



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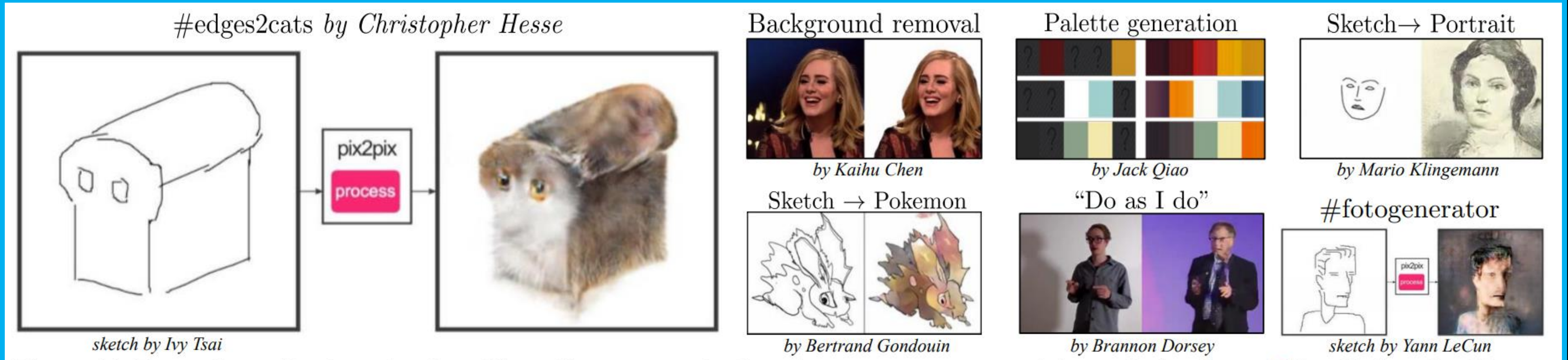

Figure 11: Example applications developed by online community based on our `pix2pix` codebase: *#edges2cats* [3] by Christopher Hesse, *Background removal* [6] by Kaihu Chen, *Palette generation* [5] by Jack Qiao, *Sketch → Portrait* [7] by Mario Klingemann, *Sketch→ Pokemon* [1] by Bertrand Gondouin, *"Do As I Do" pose transfer* [2] by Brannon Dorsey, and *#fotogenerator* by Bosman et al. [4].

Pix2Pix

- **Online demos**: affinelayer.com/pixsrv/
- **Colab notebooks**:
  - Training and using Pix2Pix on Colab: our repo / Demo1_pix2pix-keras-v2.ipynb
- **Papers**: pix2pix, pix2pixHD (with high. res.), vid2vid (with frame to frame consistency)

Style Transfer

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    - Encode one image extracting its content information, the feature responses in deeper layers of the network

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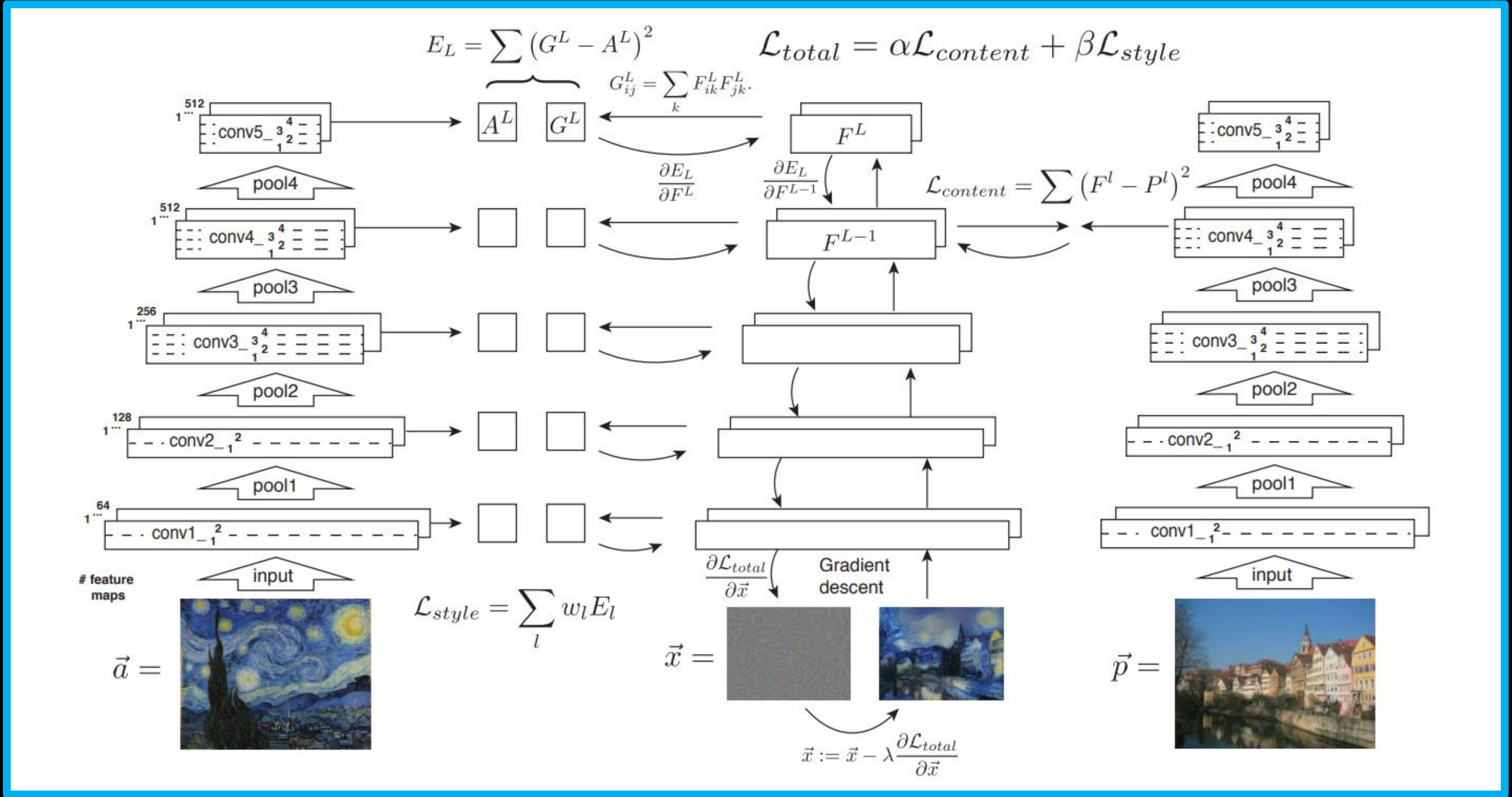
  - **High-level information** – contents of the whole image – **image content**
    - Encode one image extracting its content information, the feature responses in deeper layers of the network
  - **Low-level information** – details used inside the image, texture – **image style**
    - Encode another image extracting the style information, feature response alongside a selection of layers

(PS: One possible similarity if the content of low and high frequencies in music converted to spectrograms)

Style Transfer



Style Transfer

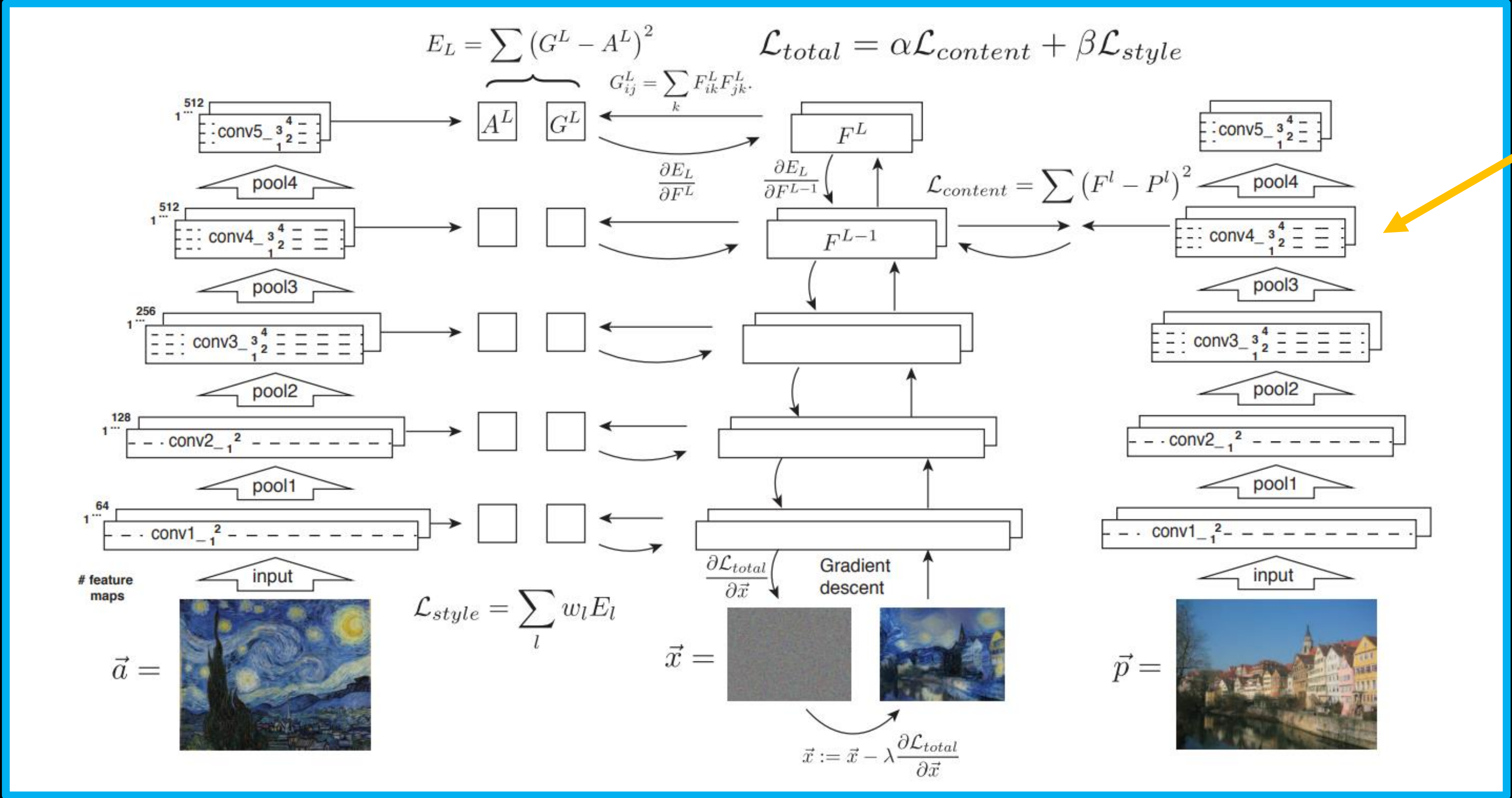
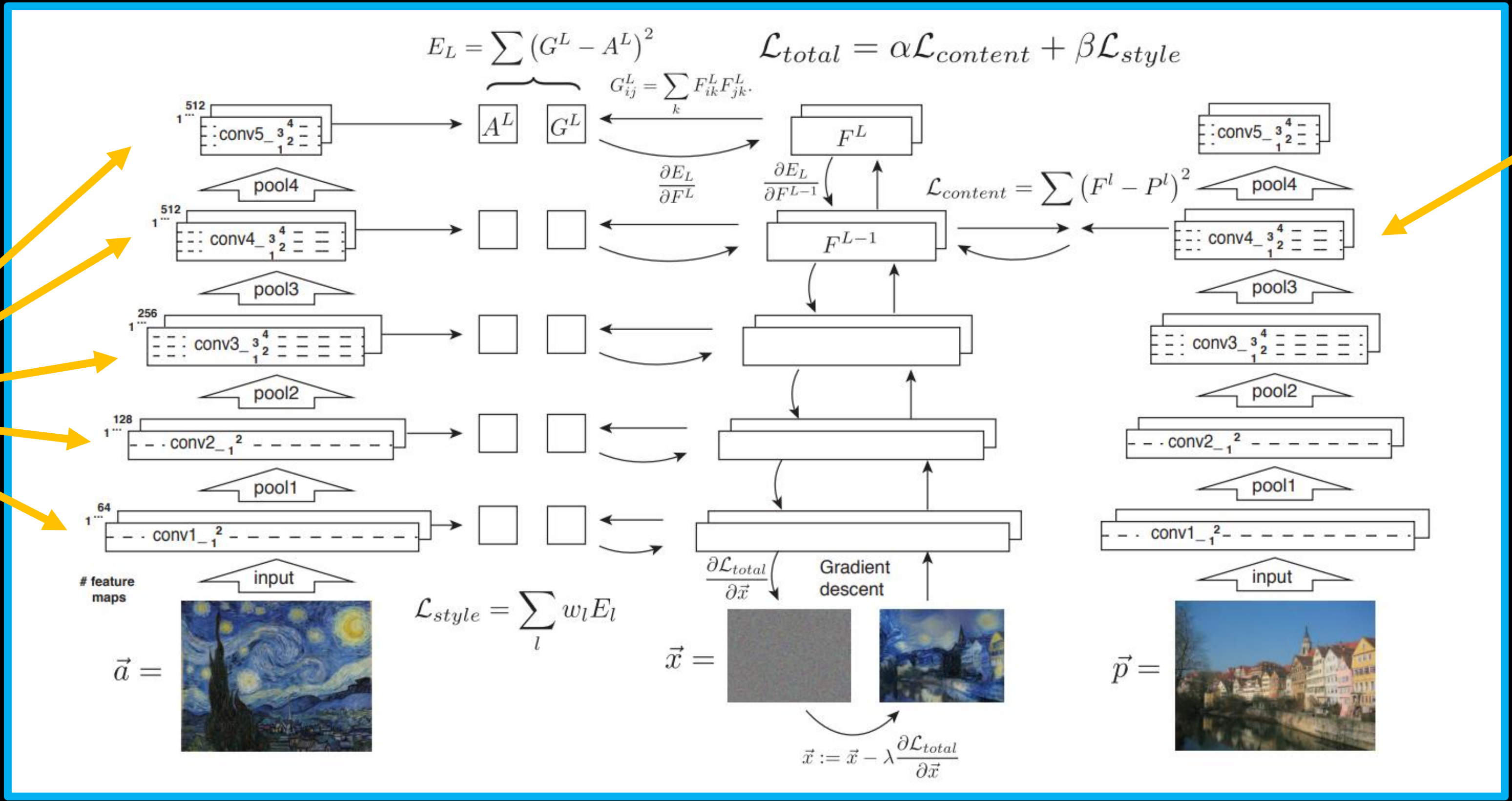


Image content = the feature responses in deeper layers of the VGG network

Style Transfer

Image style = feature response alongside a selection of layers



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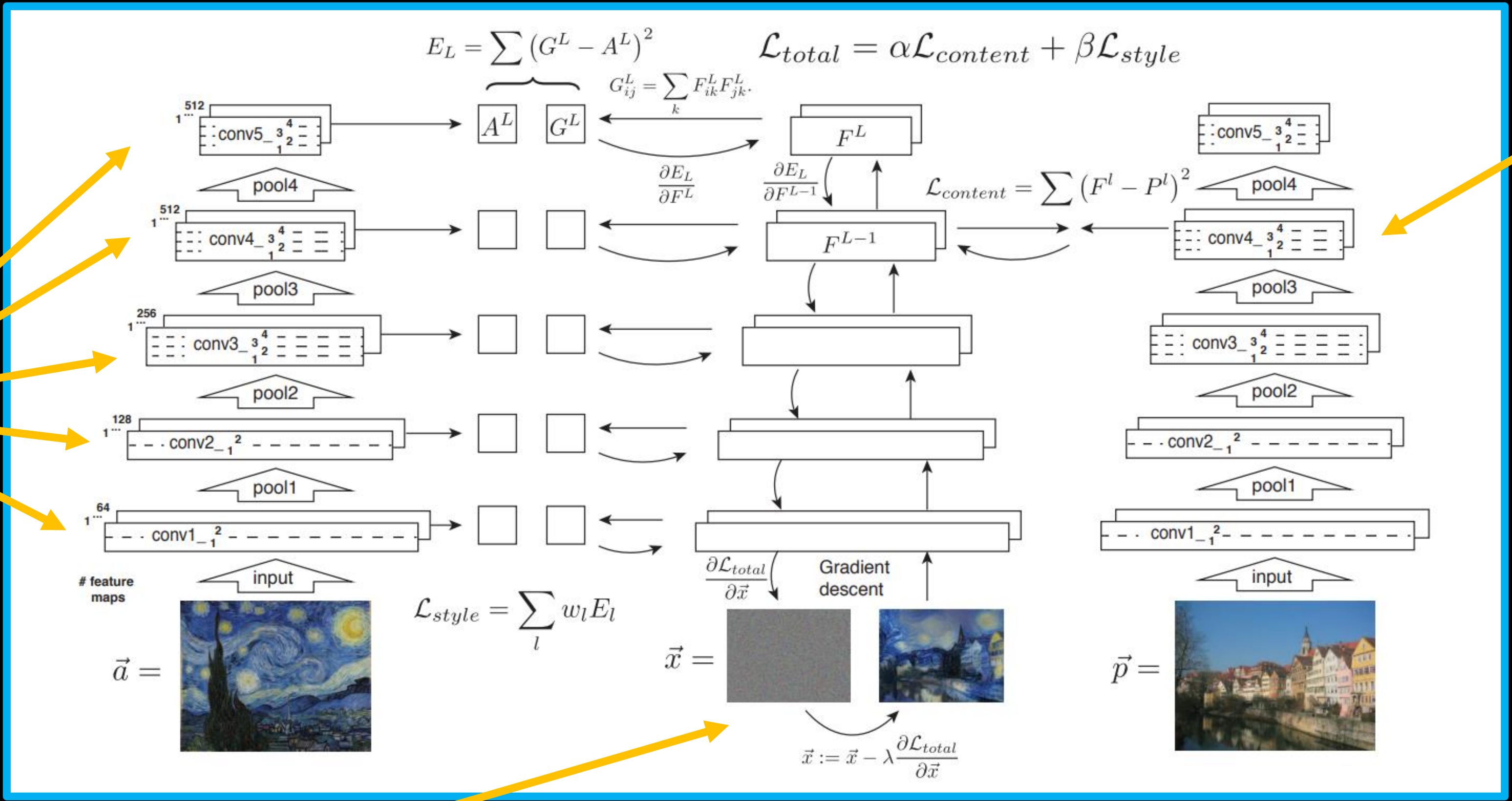

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Image content = the feature responses in deeper layers of the VGG network

Optimizing random noise image to have the same responses as those features we saved.

- Iteratively we will create a new image which has the style responses similar to our encoded style features + content responses similar to our encoded content features

Style Transfer

Image style = feature response alongside a selection of layers

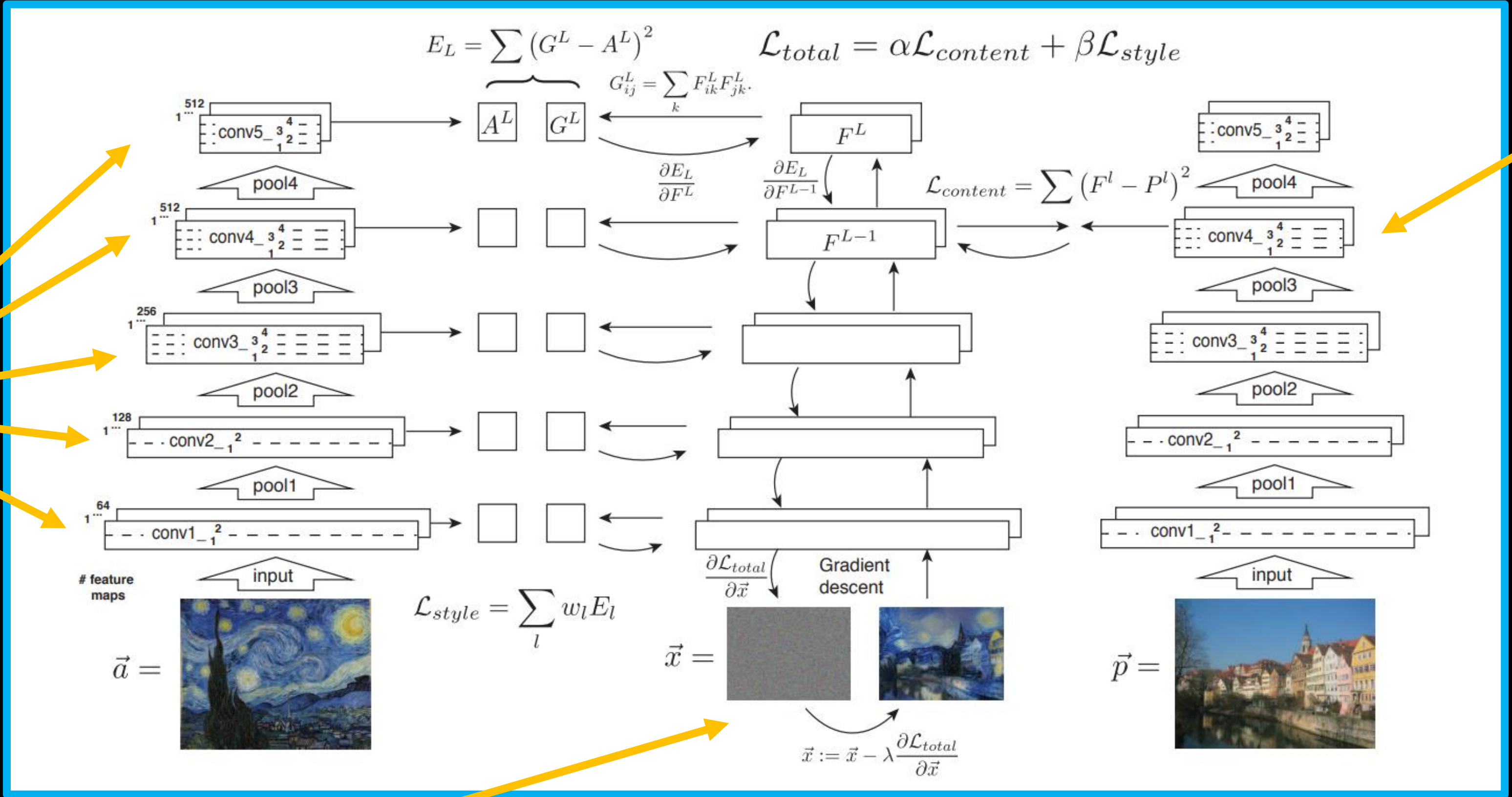

Image content = the feature responses in deeper layers of the VGG network

Optimizing random noise image to have the same responses as those features we saved.

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This is relatively slow (iterative optimization of the input image), later papers sped it up by using an image2image translation method with feed-forward networks.

Style Transfer

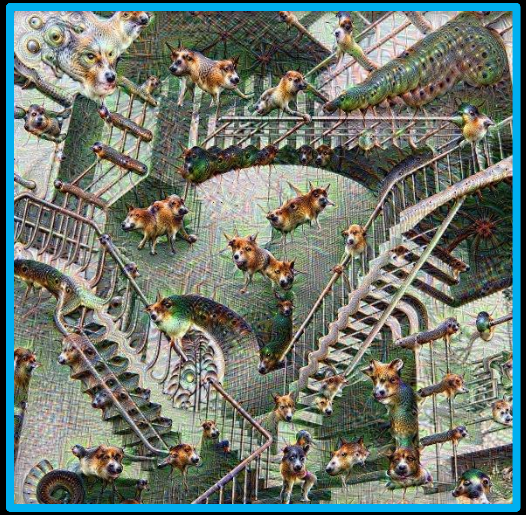
Style Transfer

- **Online demos**: deepart.io/latest/
- **Colab notebooks**:
  - Basic style transfer (with arbitrary images): ArtML / style_transfer_keras.ipynb
  - Fast style transfer (with pretrained styles): ArtML / fast-style-transfer

- **Papers**: style transfer (2015), fast style transfer (2016)

Deep Dream

- Deep dream is a method which was originally used to visualize what a network has learned. It works on image optimization principle (as did the first version of Style Transfer).



(PS: image source, features viz., illustrational video)

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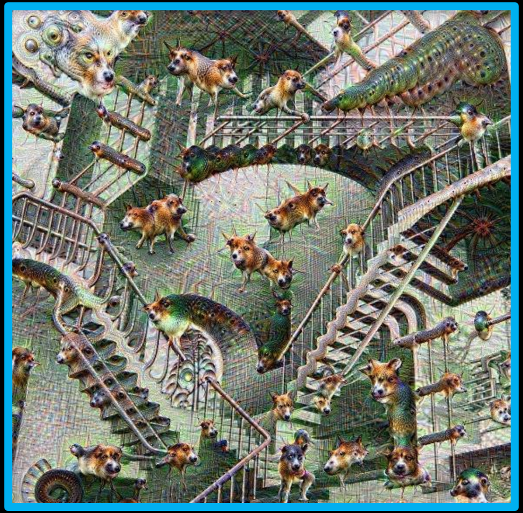
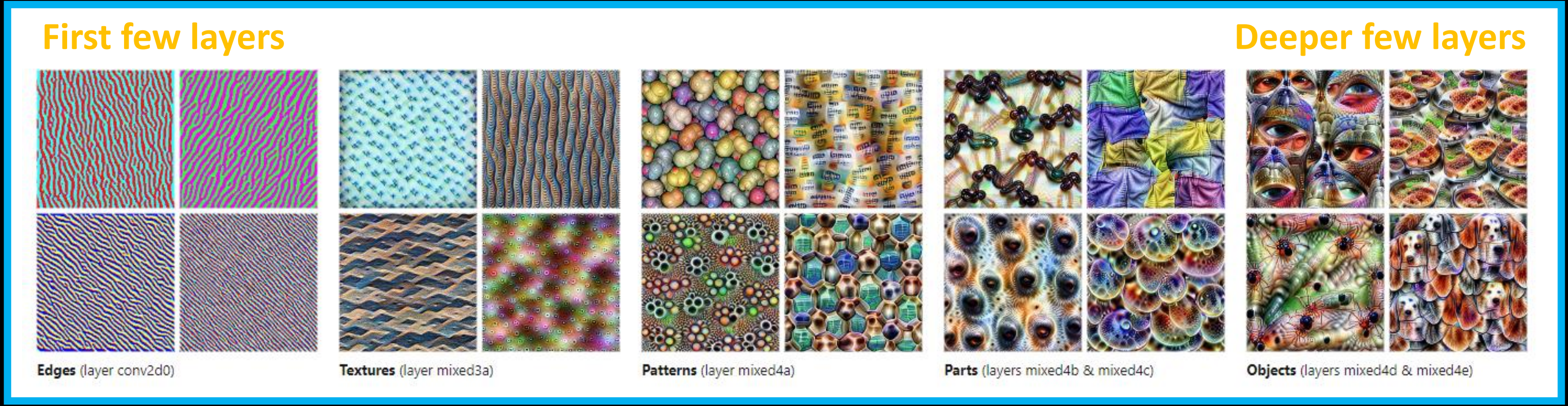


Using **Convolutional network** (GoogLeNet) trained for classification on ImageNet:



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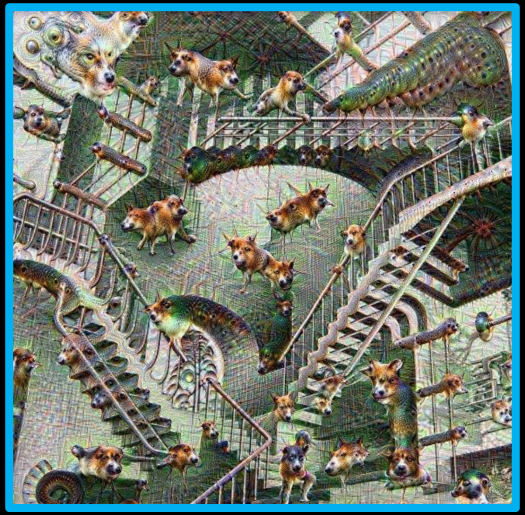
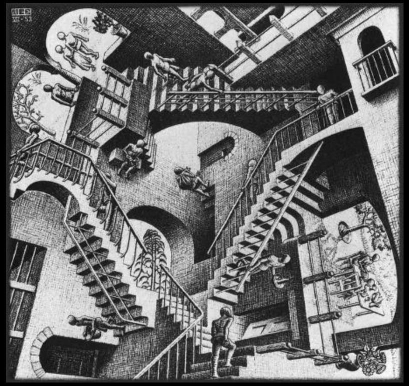


Change this **original image** so that it activates a **selected feature** with the highest possible force!



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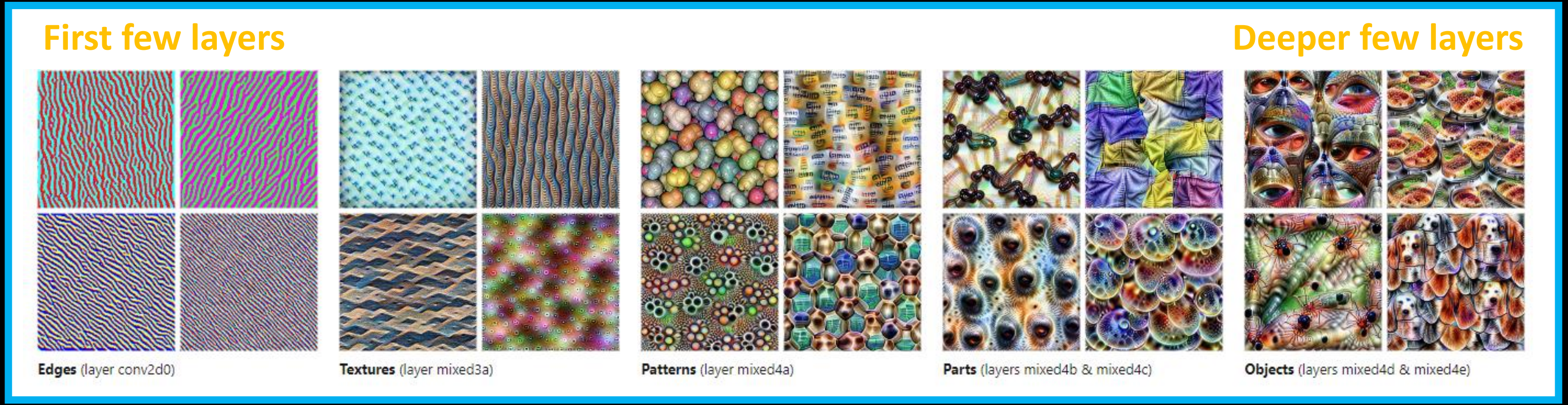

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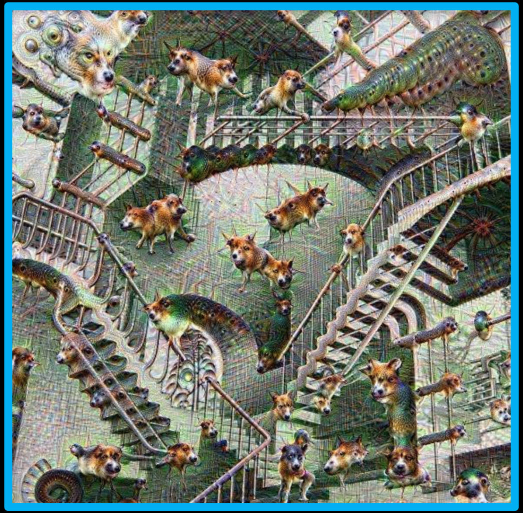

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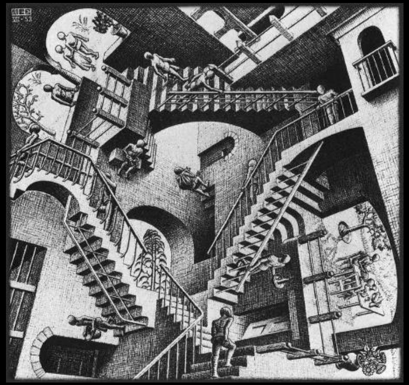

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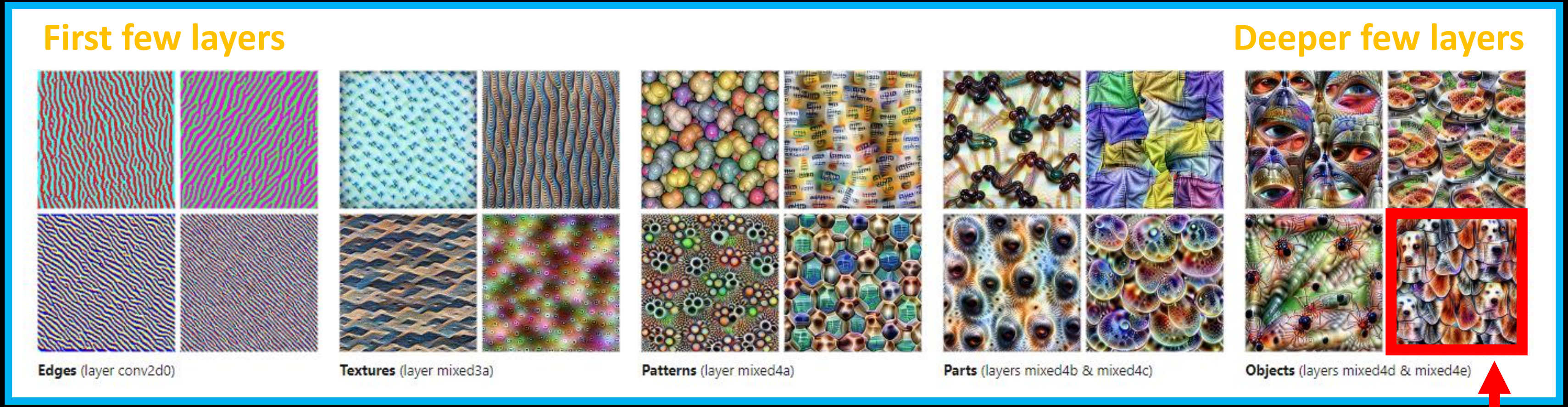

selected feature

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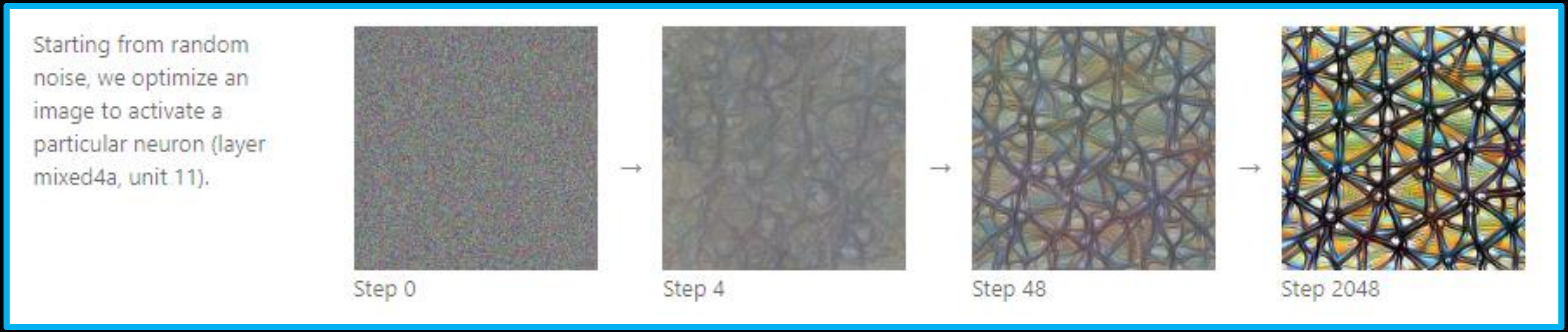
Deep Dream

Iterations:



(PS: image [source](), features [viz.](), illustrational [video]())

Deep Dream

- **Online demos**: dreamscopeapp.com *(not 100% sure if it's not a style transfer of deep dream like effect)*
- **Colab notebooks**:
  - Deep dream a photo: as a ML4A guide
  - Alternative code: ArtML / neural-synth-clustering-v2.ipynb
- **Reading**: distill.pub/2017/feature-visualization/

Practicum: Generative Models II.

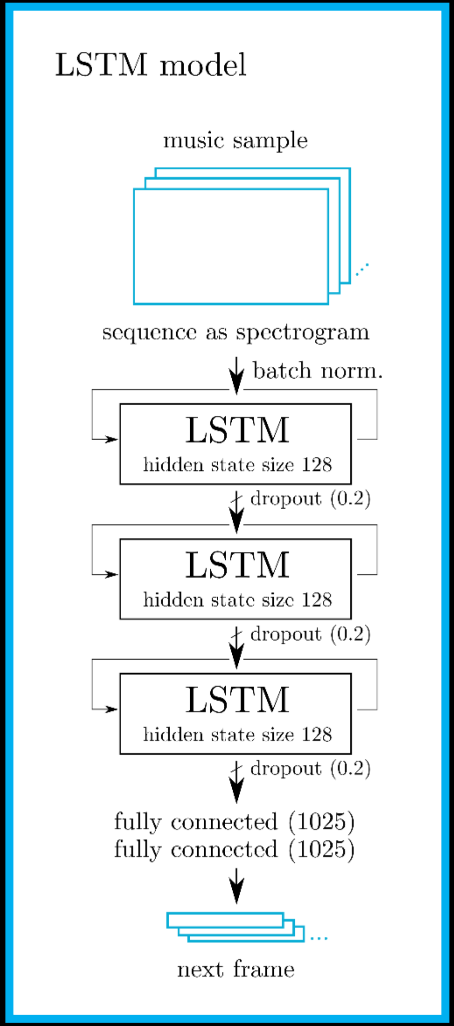
This week's focus will be in learning how to use **Progressive Growing GAN** with all practical steps included:

- data processing: 1_Dataset_Processing.ipynb
- model training and finally model inference: 2_Train_Progressive_GAN.ipynb

Next class

More generative models:

- **Sequential modelling**



Links and additional readings:

- **Bonus readings:**
  - Feature Visualization, Distill – blog
  - Sensory Optimization: Neural Networks as a Model for Understanding and Creating Art – paper
  - About Pix2Pix on ML4A – blog with code

The end