

Neural Style Transfer

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About me

- 4th year CSE undergrad
- Ex Game Developer
- ML Master race
- Information Extraction using DL

Goals of this talk

- Introduce Style Transfer (duh)
- Bring people into the DL master race
- Introduce tensorflow as python tools
- Provide something not found online

Style Transfer



Style Transfer



Ugh!



Style Transfer





Pablo Picasso





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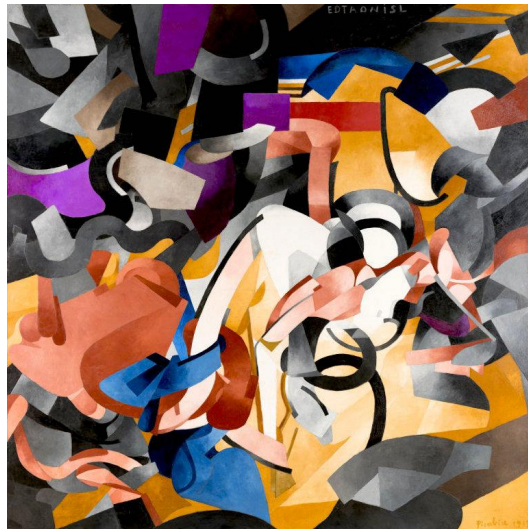


Whoa!

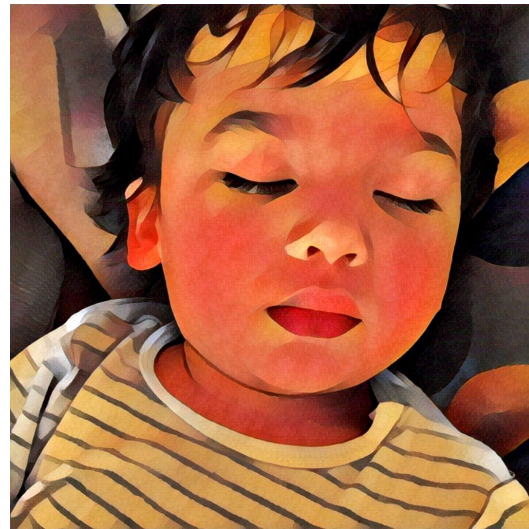
How does one go about this?



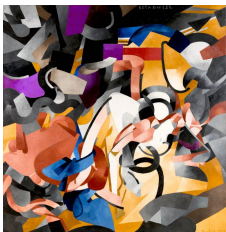
Content Image

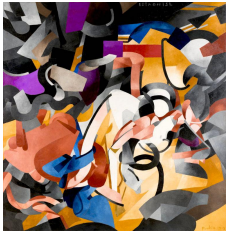


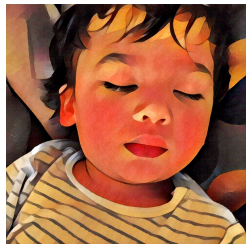
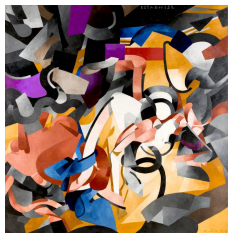
Style Image



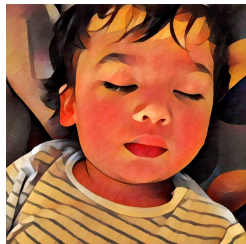
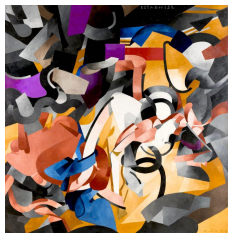
Combined Image







$$\mathcal{L}_{\text{content}} \left(\text{img}_1, \text{img}_2 \right) \approx 0$$



$$\mathcal{L}_{\text{style}} \left(\text{[Abstract Cubist Face]}, \text{[Sleeping Child]} \right) \approx 0 \quad \mathcal{L}_{\text{content}} \left(\text{[Sleeping Child]}, \text{[Sleeping Child]} \right) \approx 0$$

Optimisation

Finding an alternative with the most cost effective or highest achievable performance under the given constraints, by maximizing desired factors and minimizing undesired ones.

$$\text{Maximize : } A = 2hr + \frac{1}{2}\pi r^2$$

$$\text{Constraint : } 12 = 2h + 2r + \pi r$$

Optimisation

Finding an alternative with the most cost effective or highest achievable performance under the given constraints, by maximizing desired factors and minimizing undesired ones.

$$\mathbf{x}^* = \operatorname{argmin}_{\mathbf{x}} (\alpha \mathcal{L}_{\text{content}}(\mathbf{c}, \mathbf{x}) + \beta \mathcal{L}_{\text{style}}(\mathbf{s}, \mathbf{x}))$$

Take the average?

No

Will produce bad non-intelligent results

content and style losses are based not on per-pixel differences between images, but instead in terms of higher level, more perceptual differences between them.

We need a system which:

Understands abstract concepts like lines and shapes

Teaching such concepts is difficult
mathematically/programmatically

Enter : Deep Learning

Deep Learning would require you to understand:

- Neural Networks
- Convolutions
- Optimisation
- And on and on

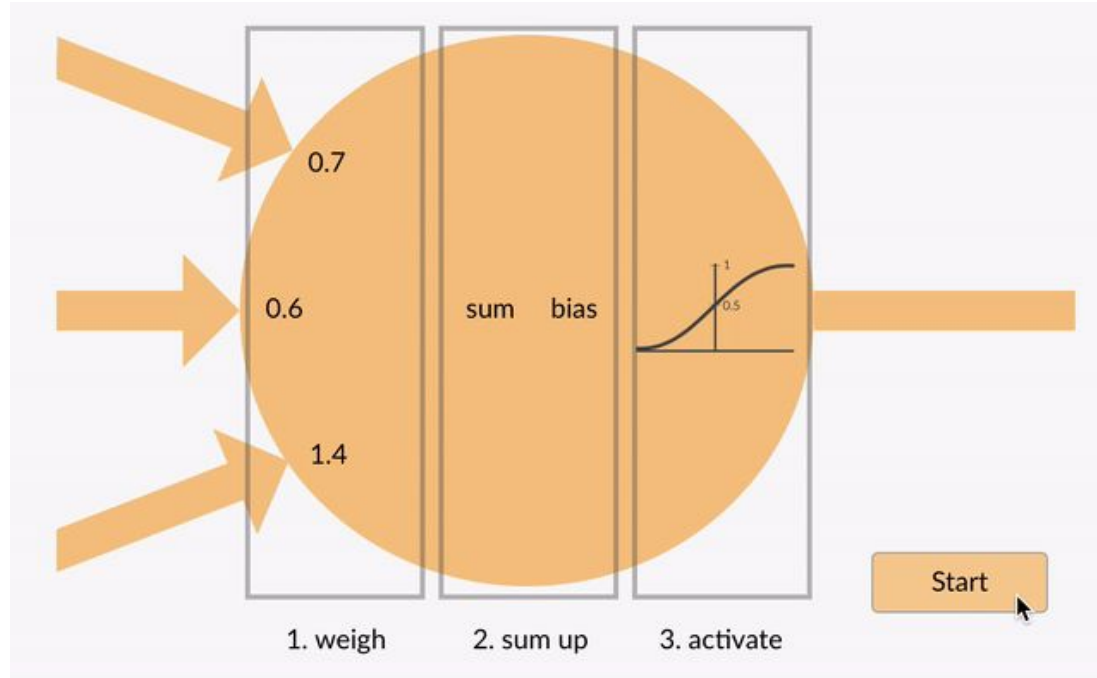
We don't have time to go through this

Solution:

Let's keep it simple.

Look at everything as an optimisation problem

But first, what is a neuron?



But what are they really?

A parameter wiggler.

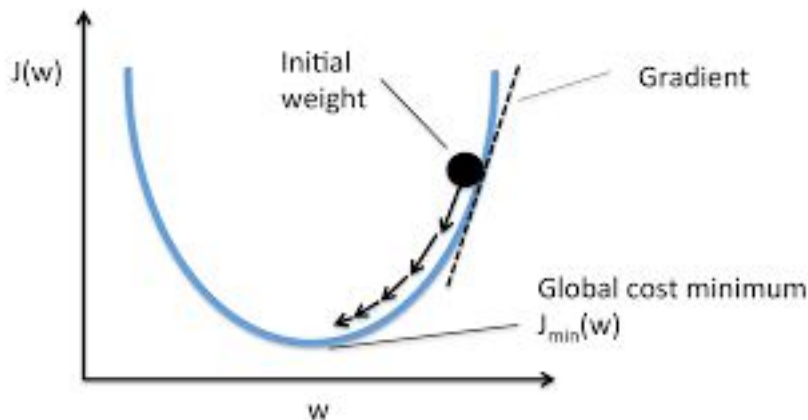
It wiggles the parameters
till it predicts correctly
I.e., till the error is minimised.



Most importantly:

The neuron decides “by itself” how to wiggle the parameters.

So, we just give it a task and it “figures out” what the correct set of parameters is.

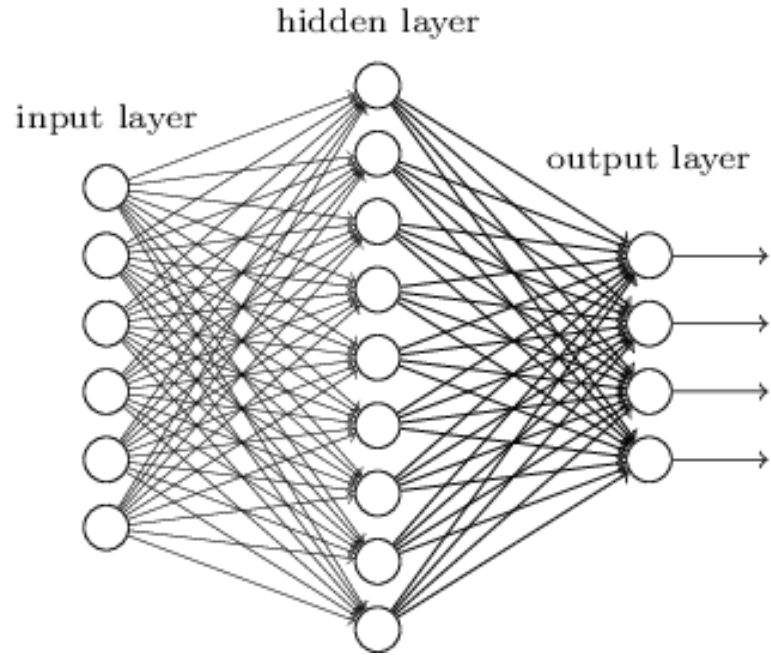


What can a simple parameter wiggler do?

Alone: not much

Combined: A lot!

This combined form is
a neural network

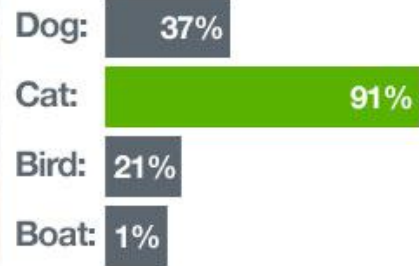
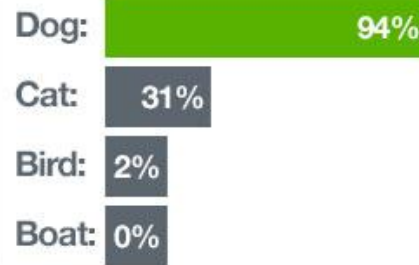
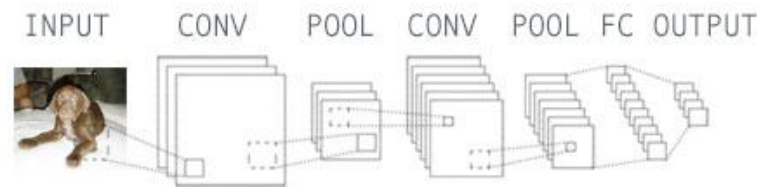


How it works

We give it an input

It predicts an output

We know the correct output



If the output is wrong we get a high error.

We let the network know:



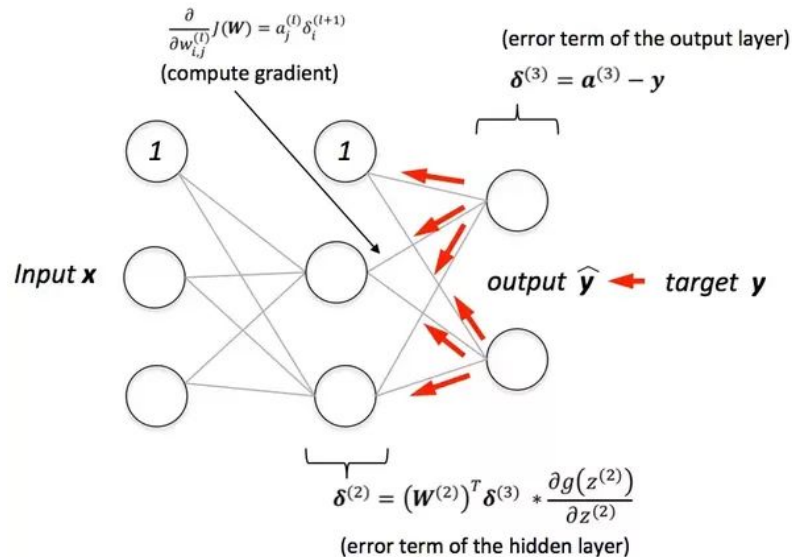
The network feels bad.
It wiggles its parameters to
reduce the error.

These photos were taken before and after
the photographer called him a good boy

@DrSmashlove



How does it learn the direction to wiggle in?



Framed as an optimisation problem

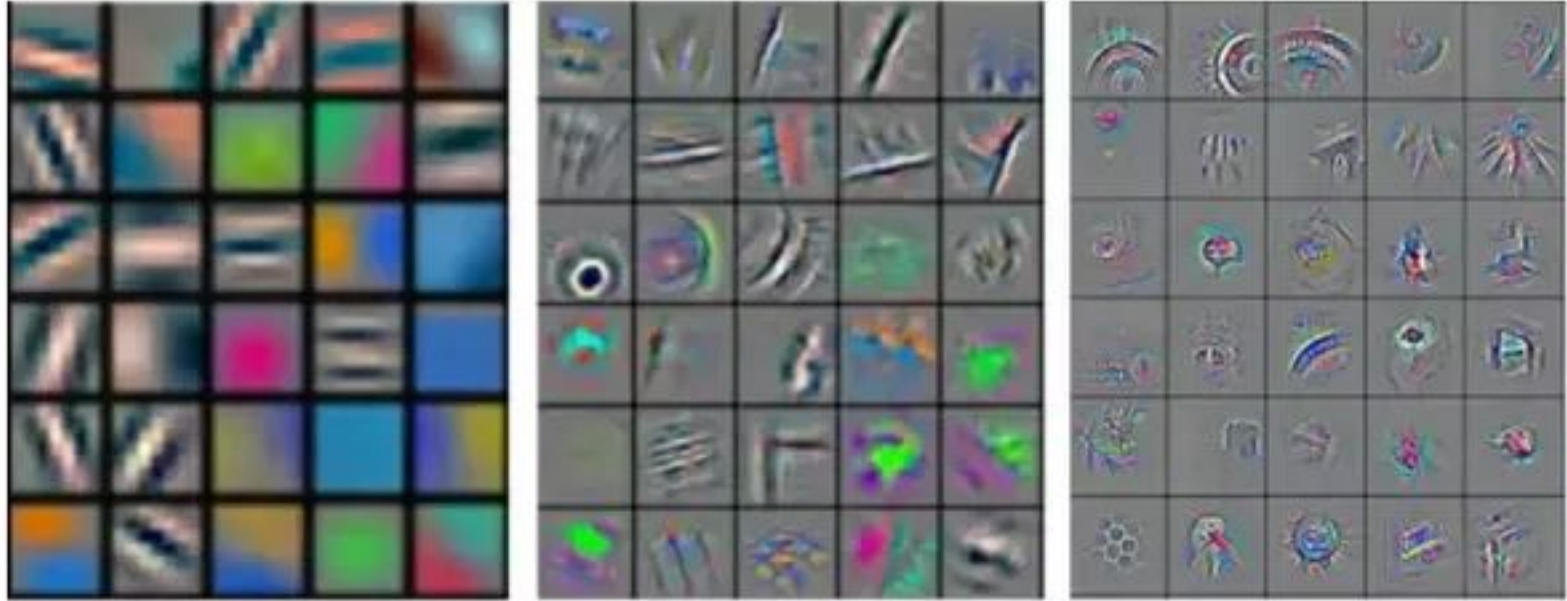
We want to minimise the error

That's it.

Let the network decide the rest.

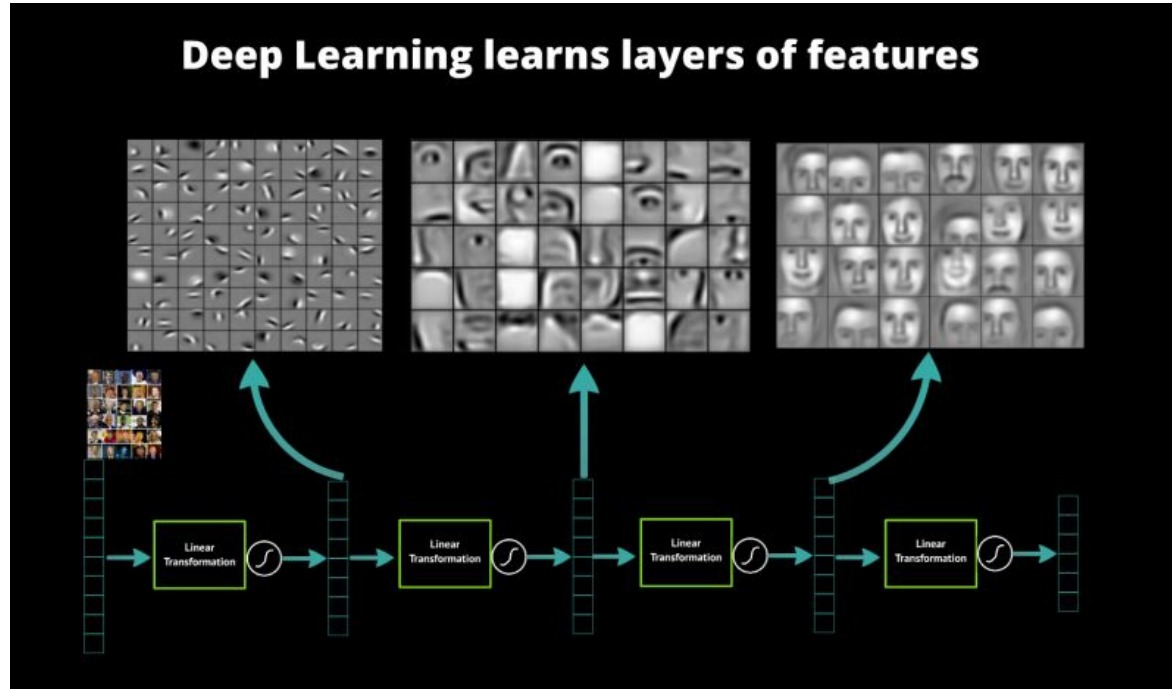
Error: distance between prediction and expected output

In the process of reducing errors, it learns interesting representations of the input data.



Learned features and their aggregation using ImageNet data

These representations are spread throughout the different layers



It extracts features because they allow it to reach its ultimate goal: to minimise error

Back to Style Transfer!

We don't care about the predictions for now

We care about the extracted features

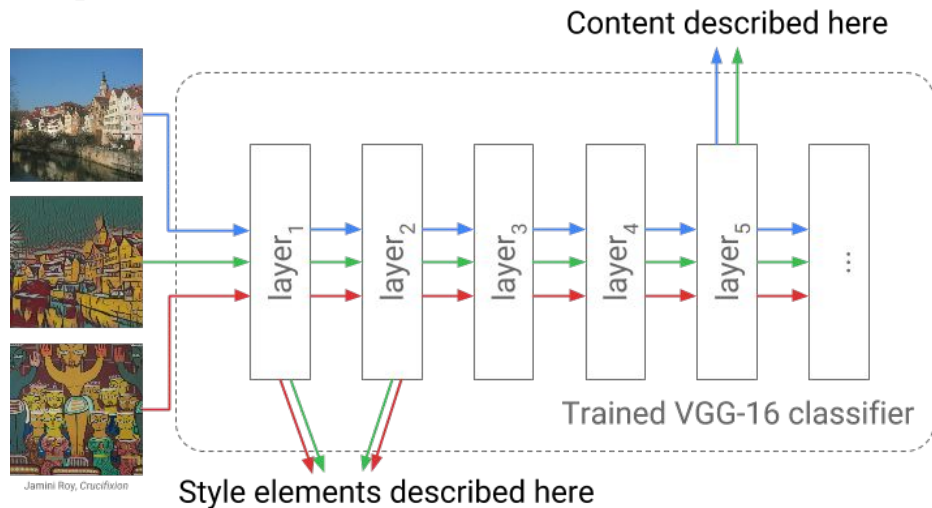
They capture abstract ideas like edges and shapes.

Perfect!

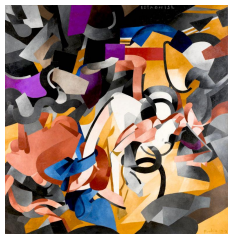
How do features help?

The features give us a way of measuring distance between images

based on features rather than pixels



We now have a way of calculating these losses in a meaningful way



$$\mathcal{L}_{\text{style}} \left(\text{[Abstract Painting]}, \text{[Painted Child Face]} \right) \approx 0$$

$$\mathcal{L}_{\text{content}} \left(\text{[Original Child Face]}, \text{[Painted Child Face]} \right) \approx 0$$

Transfer Learning

For the network to learn features, it needs to be trained on a task.

We could train our own network.

Takes time, data, machines

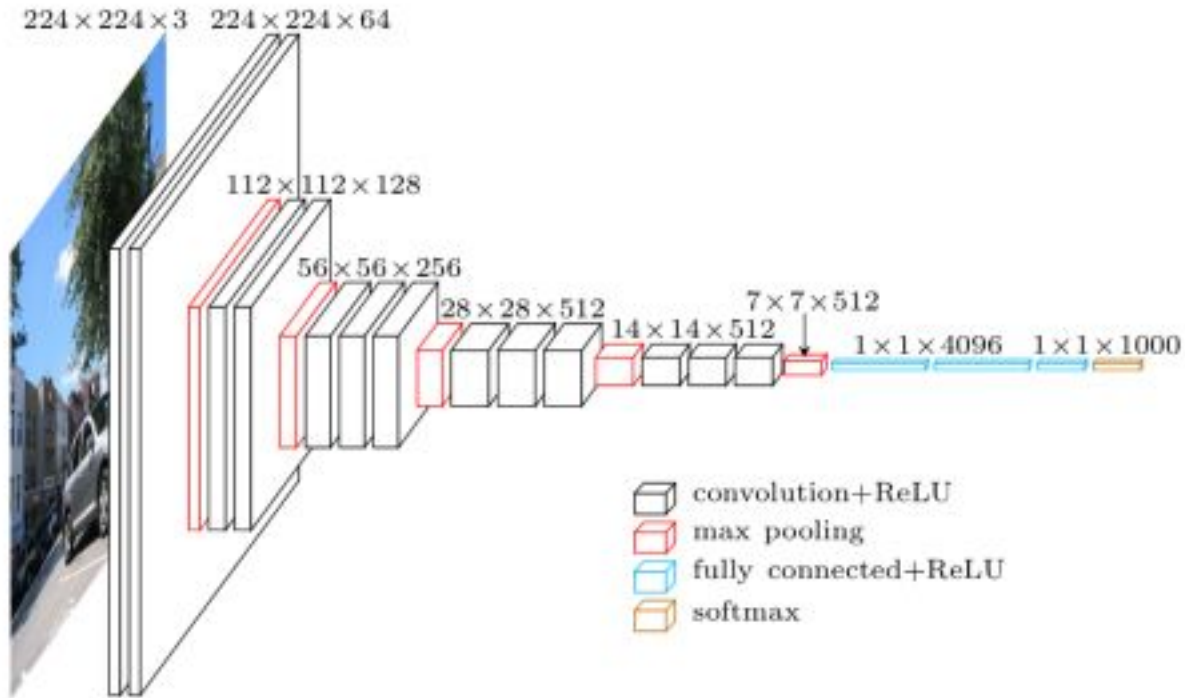
Transfer Learning

- We will use the pre trained VGG16 neural network for our task.
- ImageNet Competition
- Use 16 layers involved with feature extraction

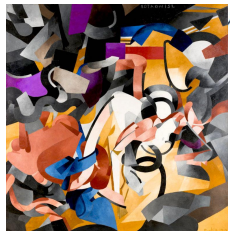
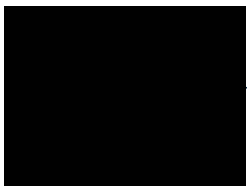
VGG16



VGG16 Architecture



Architecture



VGG16

Layer i

Content
image
features



Minimise

Distance

Combined
image
features



Minimise

Distance

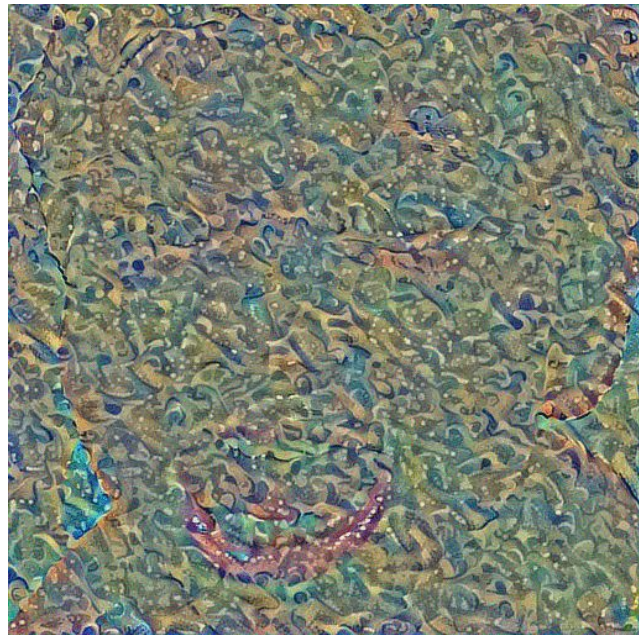
Style image
features

Content Loss

Style Loss

Total Loss

Over several iterations:

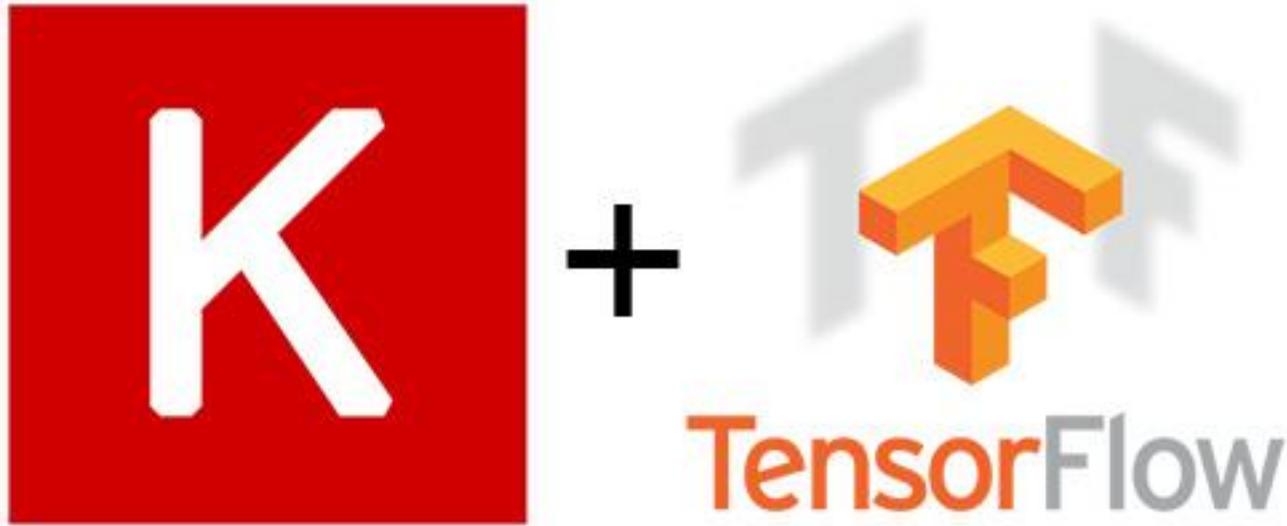




Tying it up with Python



Tying it up with Python



Thank you!