

Maximise Activations

VLC =  Vision
Learning
Control

Visualisation

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Overview

- The Electrophysical and Psychophysical Aspects of Vision
- Characterising Single Cells
- Feature Visualisation: Monkeys to Machines
 - Decorrelation
 - Reparameterisation
 - Maximising: Cells, Layers, Predictions
- Machines to Monkeys

Note

- Feature visualisation article here:
<https://distill.pub/2017/feature-visualization/>
- PyTorch implementations of key algorithms which generated the images can be found here:
<https://github.com/pytorchbearer/visual>

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- Inputs - visual stimuli
 - still images, moving stimuli, colour, greyscale, ...
- Outputs - activations
 - single cells, groups of cells, external actions, micro-electrode recordings, fMRI, ...

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- Need to restrict to some controlled stimuli space - colour? edge orientation?

Case Study: Colour Opponency

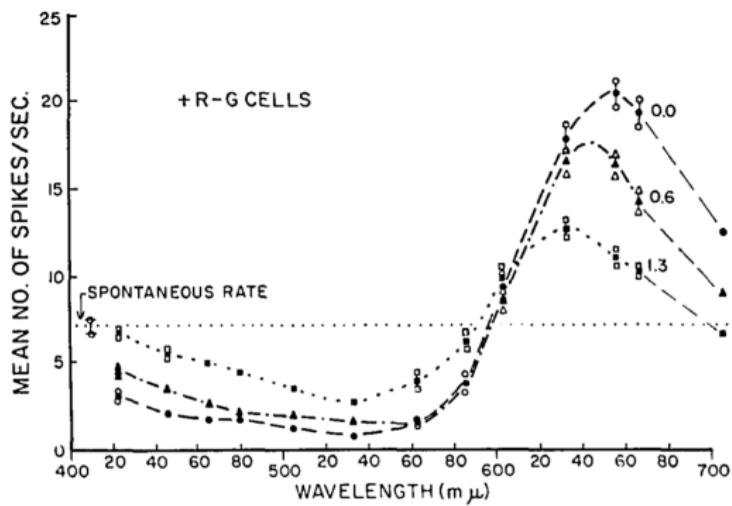
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- Consider the baseline response (or spontaneous rate) of a cell to an empty visual field (i.e. constant grey-level across the retina)
- Now, we change the colour (wavelength) of the visual stimuli and measure the response

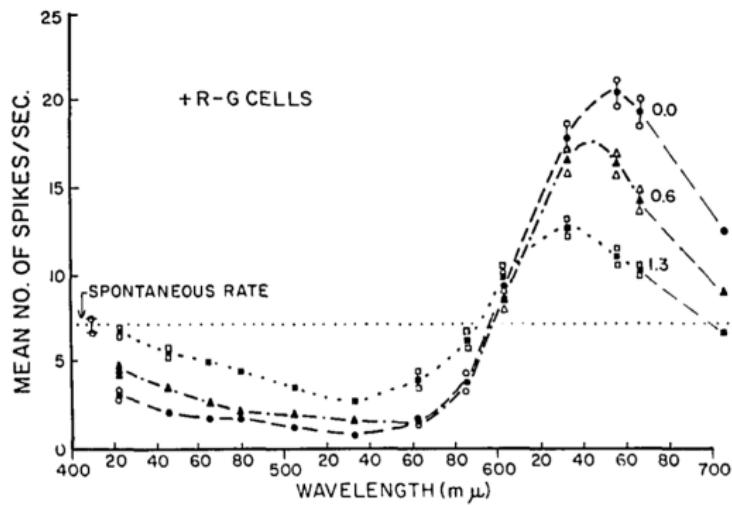
De Valois: Analysis of Response Patterns of LGN Cells

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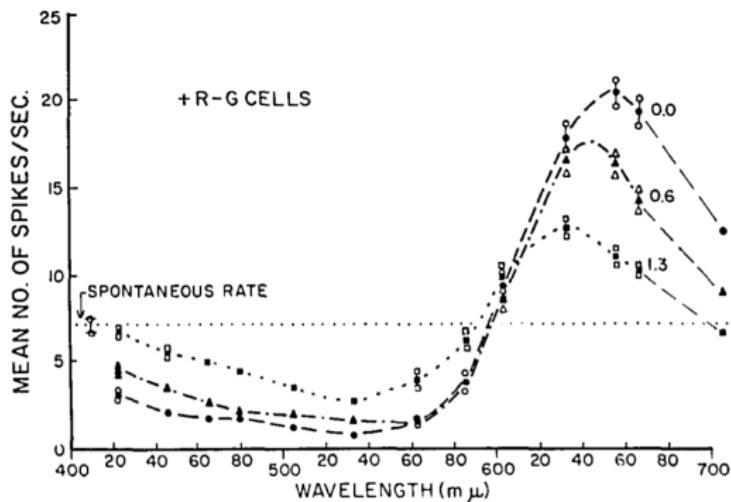
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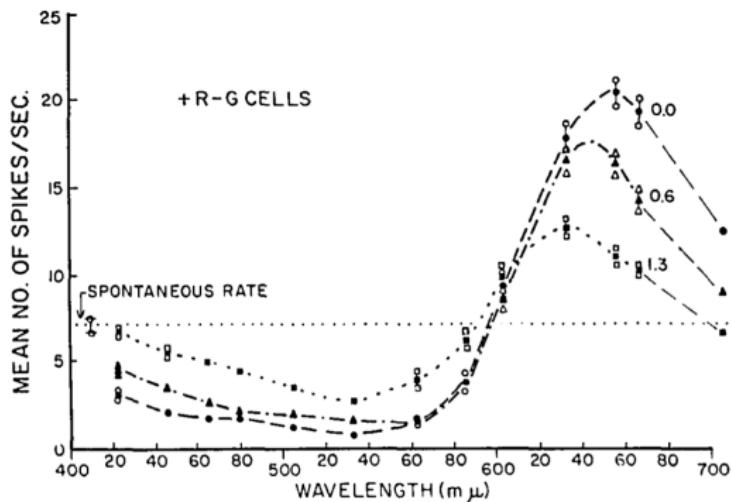
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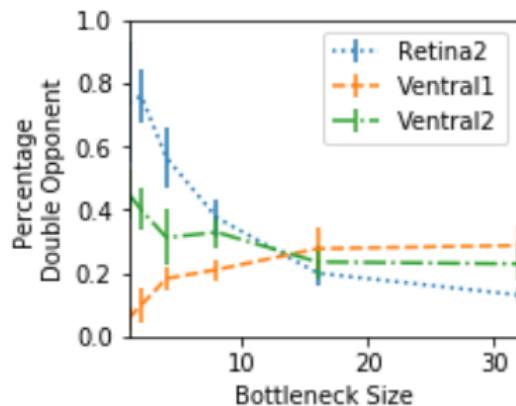
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- An analogous form of opponency can be defined - **spatial** opponency
- Cells which are both spatially opponent and colour opponent are called **double** opponent

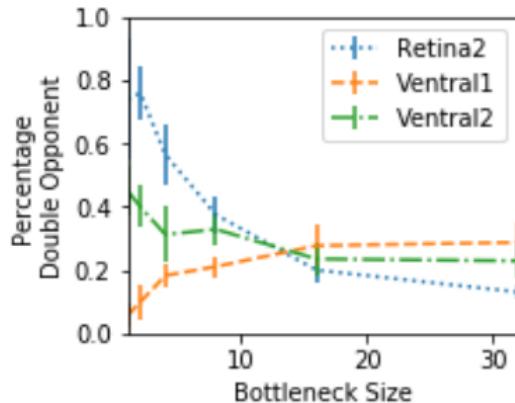
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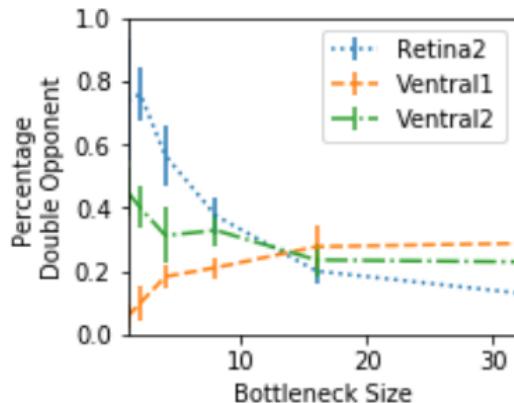
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- More here: <https://github.com/ecs-vlc/opponency>



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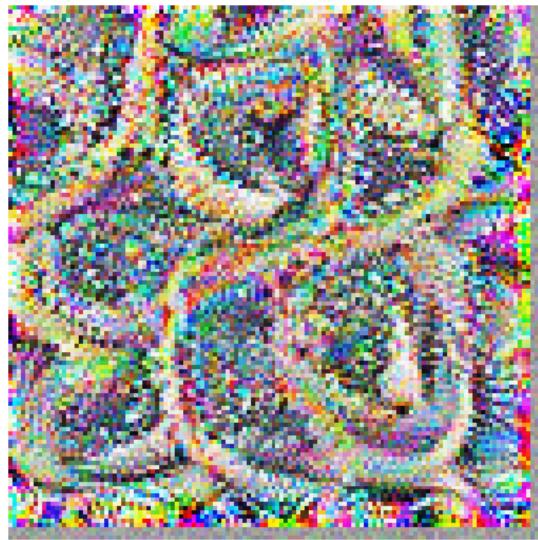
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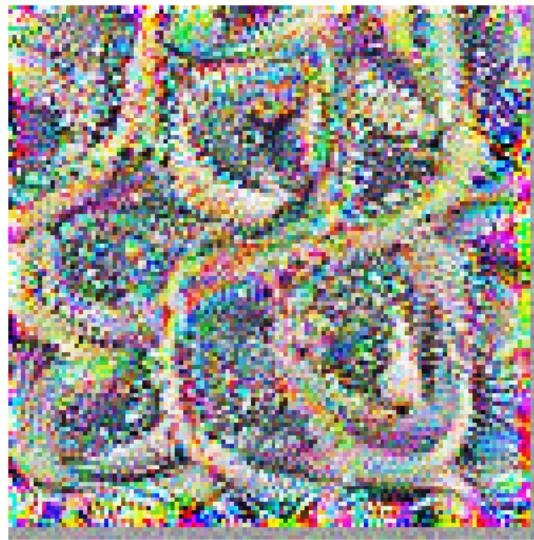
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- Gradient ascent - use the gradient information we have to 'learn' the image which maximises the response of a particular cell or channel

Gradient Ascent



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Gradient Ascent



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- Gradient ascent makes an **uncorrelated** update in a **correlated** space
- hence the crazy colours

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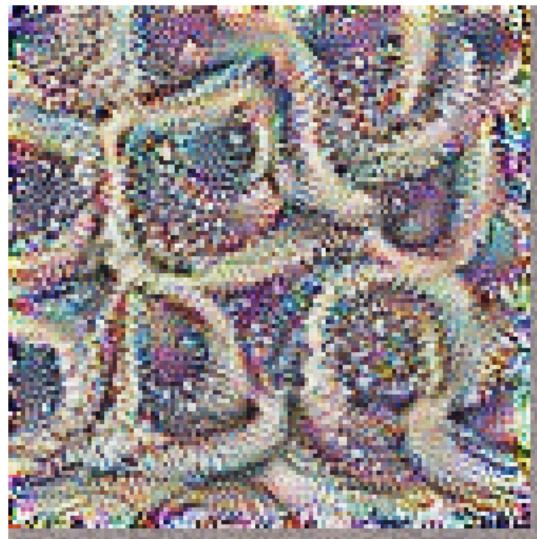
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- The maxima don't change - but the loss surface does - some optima become more likely to be found

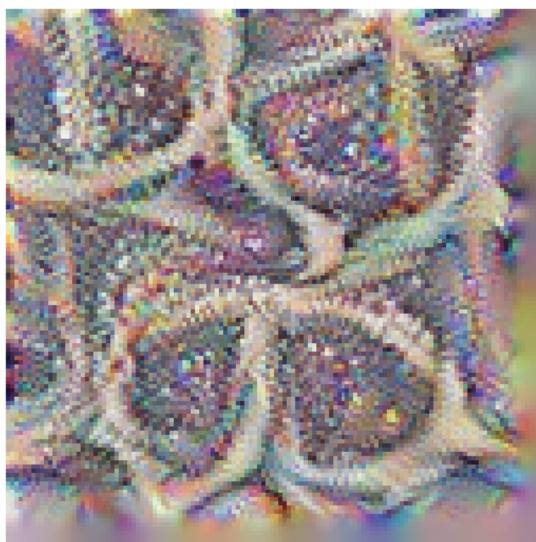
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- What can we do about the noise?

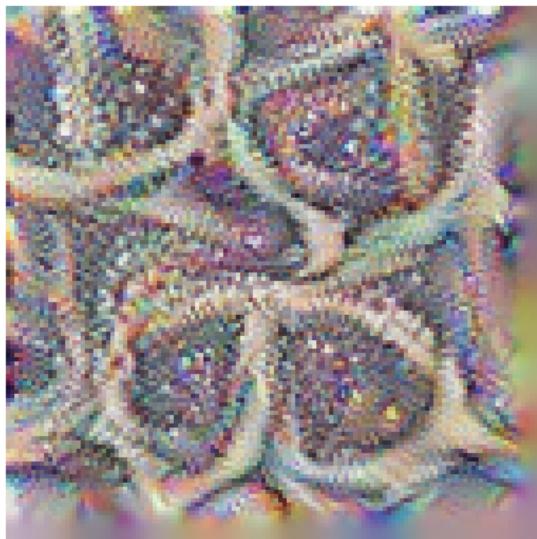
Frequency Penalisation

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 - Total variation, blur, L1 loss, ...



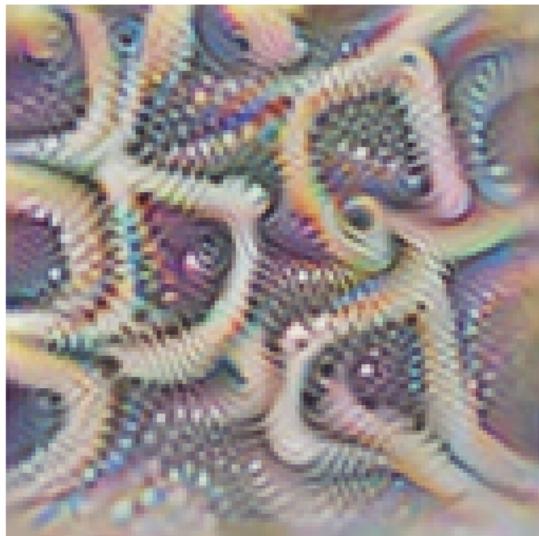
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- It's better - but we have other ways to improve optimisation procedures



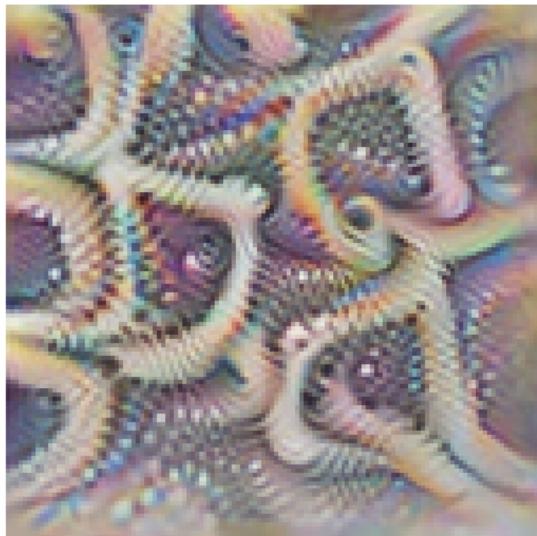
Augmentation

- Randomly transform our image before each step
- parameters → correlation → frequency penalisation → augmentation
→ model



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- We know the importance of correlation - what else is correlated in natural images?



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- The Fast Fourier Transform (FFT) is differentiable!

Fourier Space

- Fourier coefficients → parameters → correlation → augmentation → model - frequency penalisation is turned off here
- That's better!



Maximising the Outputs

- We could also maximise the outputs for a particular class
- Here's an Indian Elephant (class 385)



Maximising the Outputs

- And a Grasshopper (class 311)



Maximising the Outputs

- Or a Strawberry (class 949)
- You get the idea - deep neural networks don't learn about shape!



Maximising the Interestingness

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- DeepDream! - best results when we start with a real image and gradually increase the scale through training

Mona Lisa



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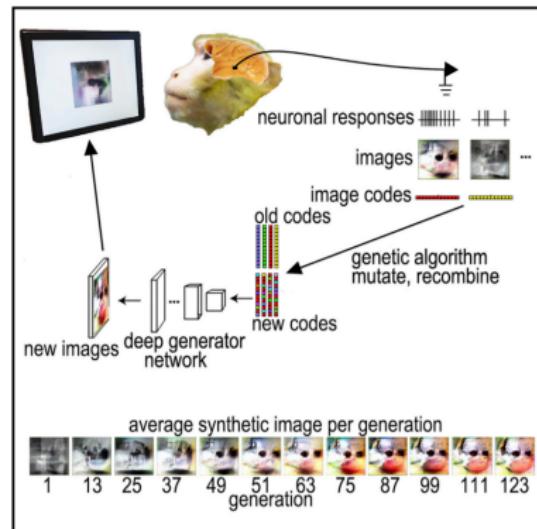
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- So we've seen how we can get great visualisations of deep networks
- Much more informative than just looking at single cells
- What's stopping us from doing this in a real brain?
- Nothing! - gradient free optimisers exist - we could use a genetic algorithm

XDREAM

- Monkey + Genetic Algorithm + Deep Generative Network



- Neurons in the Inferior Temporal cortex (AKA the ‘what’ pathway)



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- Applying that idea to deep learning we get a way to understand what each 'cell' has learned
- But be careful - feature visualisation is more of an art than a science - it isn't a completely solved problem
- Lessons and tools from deep learning can feed back in to Neuroscience, helping us to understand **much** more complex parts of the brain
- Maybe deep models and brains aren't so different after all!