Maximise Activations

VLC = ∭ Vision Learning Control dVdLdC

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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- 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?

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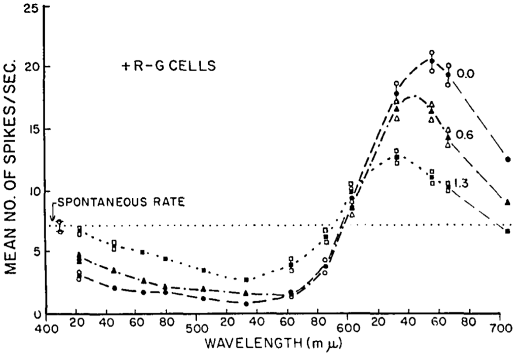
- Now, we change the colour (wavelength) of the visual stimuli and measure the response

De Valois: Analysis of Response Patterns of LGN Cells

- Macaque Lateral Geniculate Nucleus (LGN) cells



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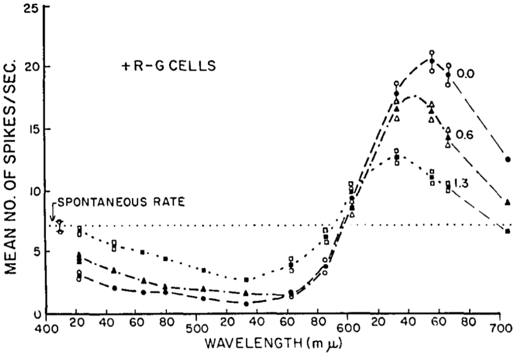

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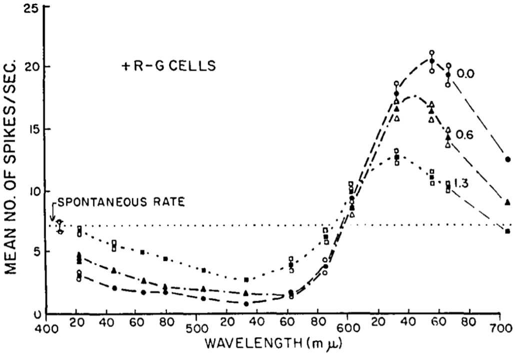

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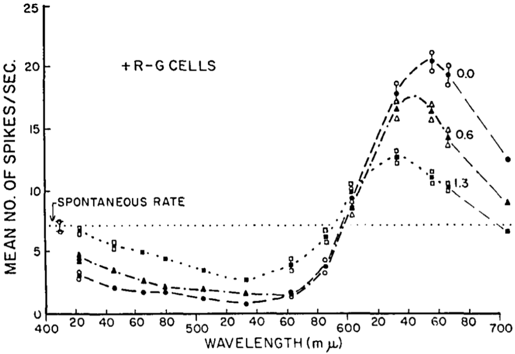

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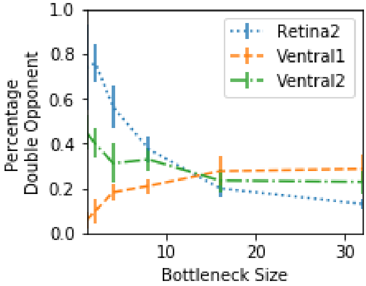
- Cells which are both spatially opponent and colour opponent are called **double** opponent

Opponency in Deep Networks

- Turns out both spatial and colour opponency happen in deep networks too!



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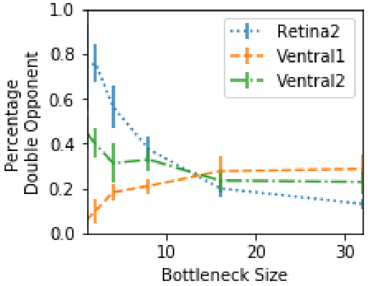

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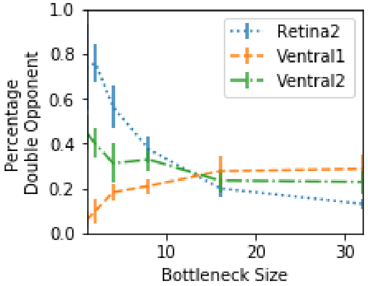
- More here: `https://github.com/ecs-vlc/opponency`



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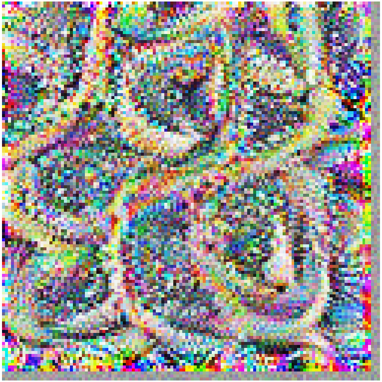
- We've shown a range of stimuli and plotted a response curve as with the monkey
- Can we do something smarter?
- Gradient ascent - use the gradient information we have to 'learn' the image which maximises the response of a particular cell or channel

Gradient Ascent



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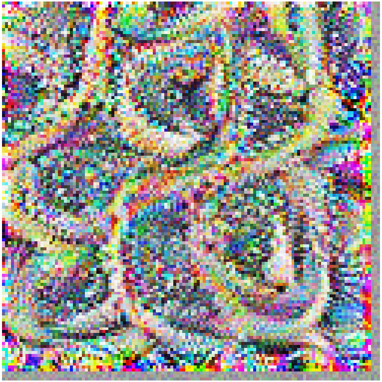

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- Gradient ascent makes an **uncorrelated** update in a **correlated** space - hence the crazy colours

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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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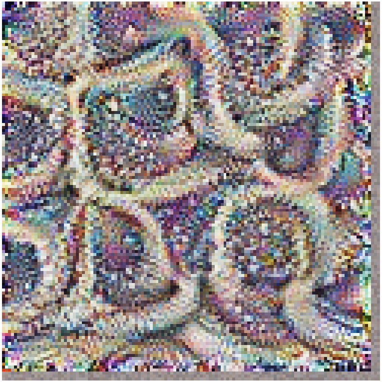
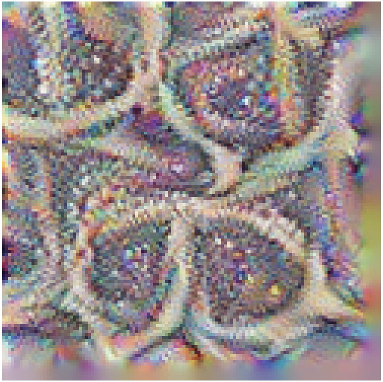


- What can we do about the noise?

Frequency Penalisation

- We can construct additional loss functions that penalise high frequencies
  - Total variation, blur, L1 loss, ...



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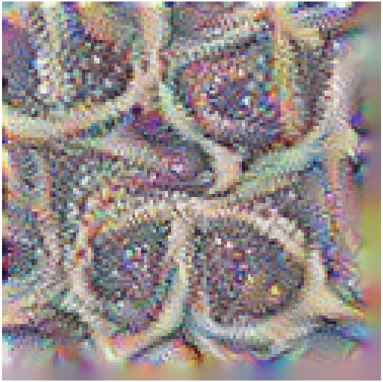
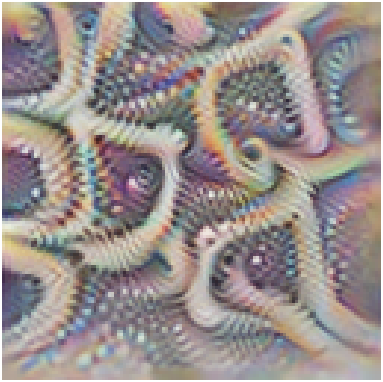
- It's better - but we have other ways to improve optimisation procedures



Augmentation

- Randomly transform our image before each step
- parameters $\rightarrow$ correlation $\rightarrow$ frequency penalisation $\rightarrow$ augmentation $\rightarrow$ model



Augmentation

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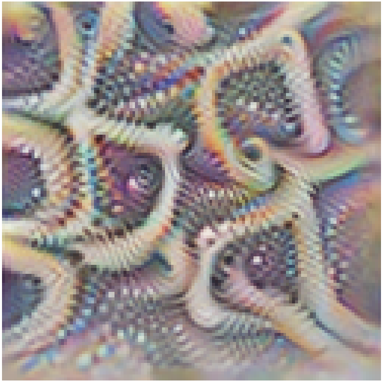
- We know the importance of correlation - what else is correlated in natural images?



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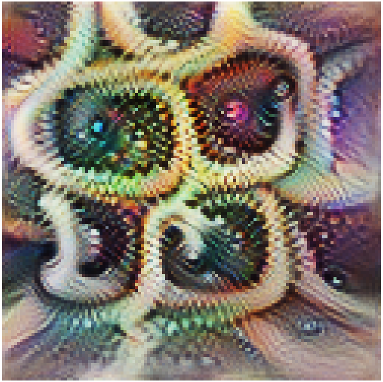
- The Fast Fourier Transform (FFT) is differentiable!

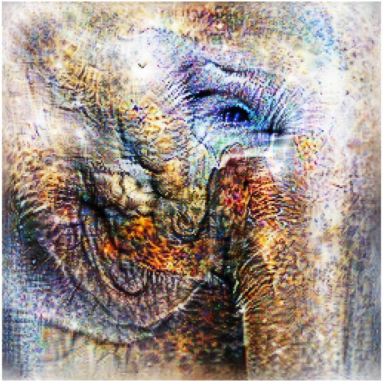
Fourier Space

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



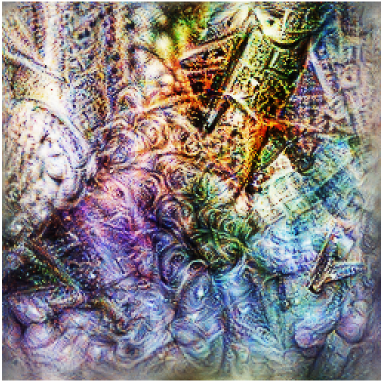
Maximising the Outputs

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



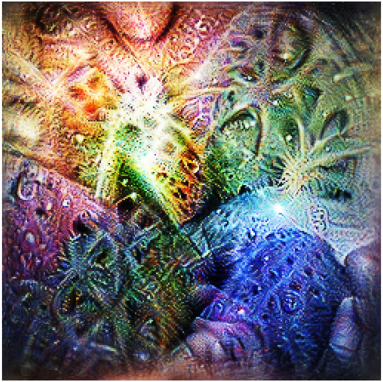
Maximising the Outputs

- 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

- What if we maximise the sum of the squares of the outputs from a whole layer?

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

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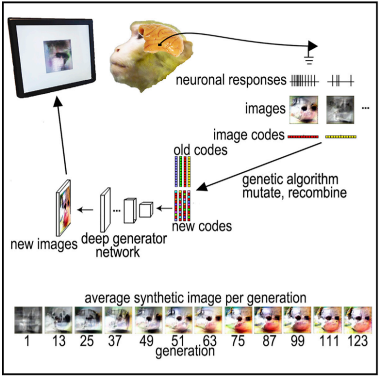
- So we've seen how we can get great visualisations of deep networks
- Much more informative than just looking at single cells
- What's stopping us from doing this in a real brain?
- Nothing! - gradient free optimisers exist - we could use a genetic algorithm

XDREAM

- Monkey + Genetic Algorithm + Deep Generative Network



XDREAM

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

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- 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!