(Human) Network Analysis

Lecture 3: **Feedforward visual processing**

Ben Harvey

1

In the last class, we discussed how the computations performed by neurons in the brain represent and process information, and how these computations provides the inspiration for operations performed in deep convolutional machine learning networks.
-We saw in the first class that there is a big difference between the operations that a network unit or layer can perform and the emergent properties of the whole network.
-Today we are going to look at how the properties we saw in the last two classes scale up to determine the properties of whole networks

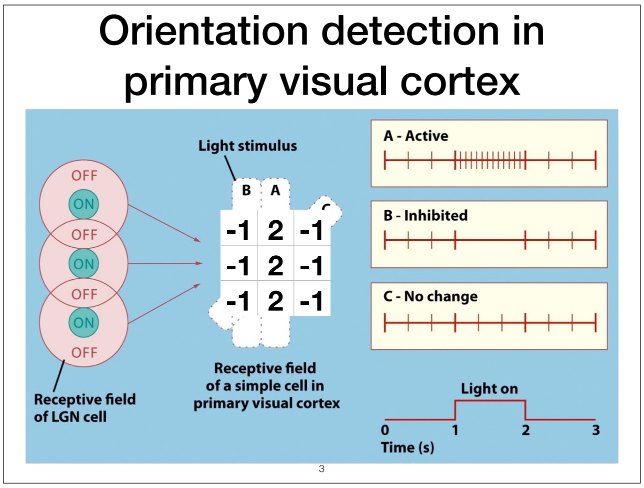
Why study vision networks?

- Image processing is a common application of artificial deep networks
  - Particularly object recognition
- Vision is well understood
  - Visual input is easy to control
  - Good animal models of human vision
  - Computational aspects are well understood
- Common application of DCNN as simulations of neural processing

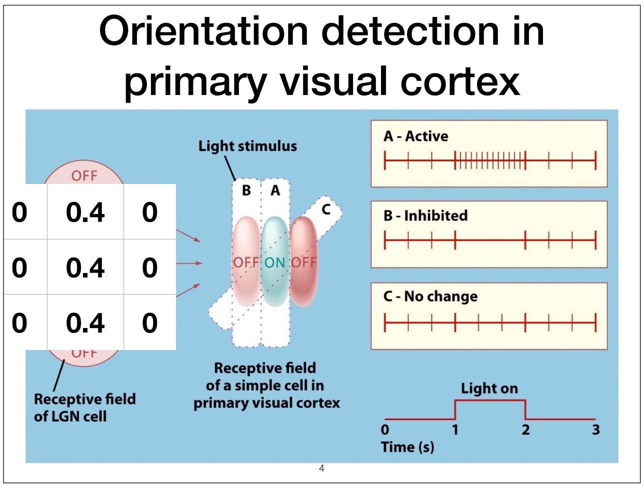
2

-We used the early human visual system as an example network, for various reasons.
-First, computer visual problems like object recognition are exceptionally difficult to solve using formal rules, and so have been an excellent application for artificial deep networks.
-Second, the early visual system is probably the best understood system in the human brain, at the computational level: we really understand HOW the brain works here. This is largely because it is very easy to precisely control visual input, and because we have good animal models of the visual system.
-Third, and related, early visual responses are a common application of DCNN as simulations of neural processing.
-However, we believe that very similar principles operate in other networks in the brain. It's just that when we scale up to look at a whole network it is very helpful to look at a specific example.

-We already saw how the retina separates images into multiple feature maps for different colours and spatial frequencies.



In our first class we saw that the first image filters the artificial networks learn are edge detectors.
–But we saw in our last class on the retina that the first receptive fields compare the activation of photoreceptors in a centre region and a surround region. These respond best to a point of light in the centre, and a line of any orientation will activate this retinal ganglion cell similarly.
–Responses to specific edge orientations first emerge in the primary visual cortex, or V1, the first area processing vision in the brain. These cells respond when an edge has a specific orientation (the preferred orientation) and is shown in a specific position.
–Orientation selectivity can be built up from spatial interactions between different centre surround cells. This group of three all need to be active for this filter to respond, and the neighbours must be inactive.
–The corresponding convolutional filter might look something like this, if it was operating in the image input.



–But remember that this filter is not operating on image inputs. The inputs to this filter are neurons and already have suppressive surround organisation.
–So, expressed as transformations of the summation of these inputs, it might look more like this: all of these inputs need to be active to reach a threshold of one.
–The inhibition is already built in by the activity of these input cells: they will be inhibited by light in the wrong place.
–Even at this early stage, it is misleading to think of these filters operating on image inputs. The inputs are already outputs of the previous layer of filters.

Orientation detection in primary visual cortex

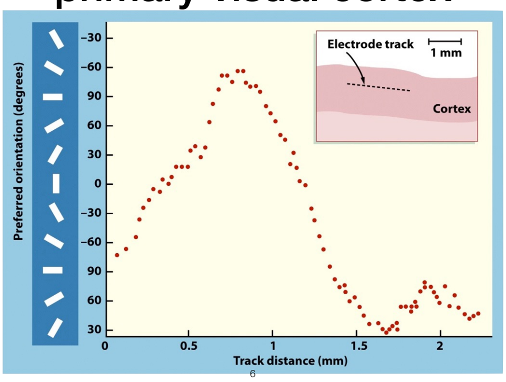
Image input

Feature map input

5

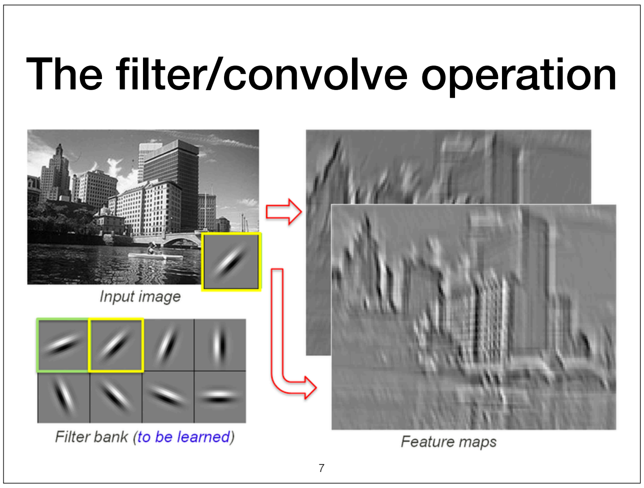
Unfortunately, humans are bad at thinking like this, in terms of transformations of neural representations rather than transformations of images.
-Conveniently, neurons and computers do not have this limitation: they transform whatever input they are given.
-At this early stage, we can easily make an image that gives an idea of where the contrast in the image is, the pattern of outputs in a feature map from the retinal ganglion cells.

Orientation organisation in primary visual cortex

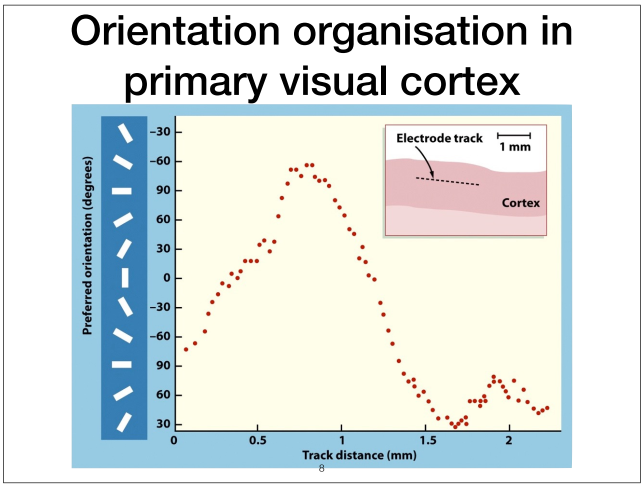


6

At a coarse scale, neurons processing the same part of the visual field are grouped,
-And neurons with similar orientation tuning are also grouped together. But this grouping is at a very fine scale, the scale of the cortical column. Each column contains neurons responding to the same position, but different orientation.



We have seen this separation into feature maps for different orientations before…

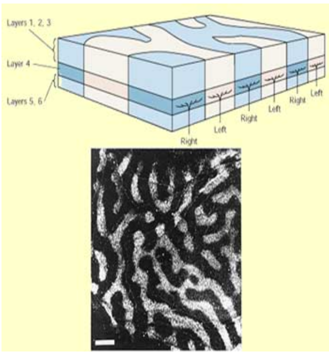


–So these different orientation columns form further feature maps.
–However, in a biological network, these orientations can have any value: they are not limited to a small fixed number of discrete filters and feature maps.
–Instead, it's more like orientation is an entire third dimension of a feature space, with position forming the other two dimensions.
–So neighbours in this third dimension have similar responses, and filters may have a meaningful extent in this third dimension.
–This is not the case in artificial deep networks, where filters typically span all feature maps in a layer and can learn any relationship between different feature maps.
–However, if analysing relationships between nearby feature maps is most useful to task performance, filters can develop that have very low weights on 'further' feature maps, which will have an effect of focussing on relationships between 'nearer' feature maps

Orientation selectivity

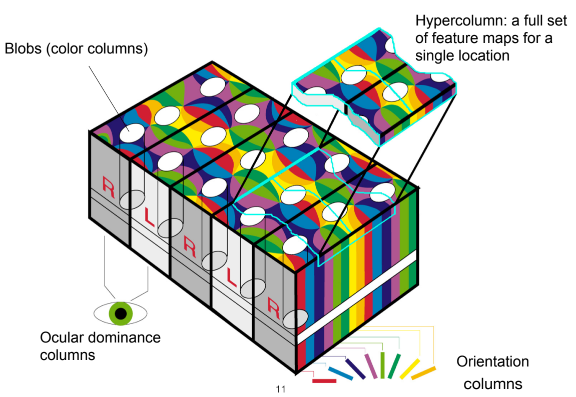
- Contrast is initially computed in an orientation-independent filter
  - In the retinal ganglion cell
  - Artificial DCNNs often avoid this step, going directly from image to edge orientation
- Orientation-selective responses are computed in V1 by operations comparing these retinal ganglion cell outputs
  - Not image brightness
  - Retinal ganglion cells essentially signal contrast
- Orientation preferences gradually change across the cortex
  - At a much finer scale than the spatial visual field maps
- This squeezes multiple feature maps into the same 2D cortical surface
  - This may arise to optimise connection lengths

Binocular integration



Primary visual cortex also receives separate inputs from the two eyes, doubling up the feature maps
–These are initially kept separate, as distinct cortical columns for the left and right eyes. Various methods can mark the parts of V1 receiving input from one eye, which forms a distinct pattern of interlaced columns, or feature maps from the two eyes.

Intermixed feature representations



These different elements effectively form several distinct feature maps that are all mixed together at the same cortical location.
–A full set of all feature maps for a single image location is called a hypercolumn, and takes up about 2x2mm of the cortical surface.
–This holds all of the transformations of this image location that have been extracted by this stage.

Elements in Scene Recognition

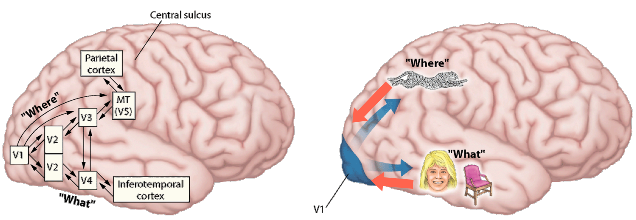
So we have separate responses to colour, orientation and even motion in different neural populations in the primary visual cortex, V1. We normally perceive all of these together.

V1 feature maps

- Colour (red, green, blue yellow, light, dark)
- Eye (left, right)
- Spatial frequency (continuous)
- Orientation (continuous)
- Motion direction (continuous)

In V1, we therefore have a very large complex set of feature maps, with each feature represented at all spatial positions.
As a result, V1 is very large.
This set of feature representations forms the input into subsequent processing stages

Visual pathways beyond V1

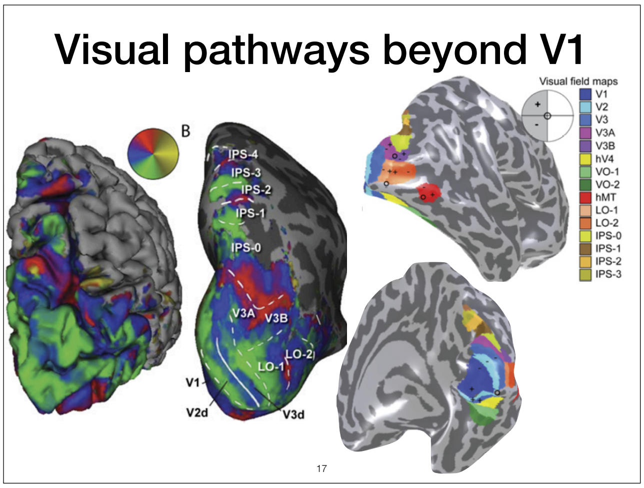


Midget-Parasol becomes What-Where
Form and color vs motion and space
Or Recognition vs Action
Or Ventral vs Dorsal
or Temporal vs Pariatal

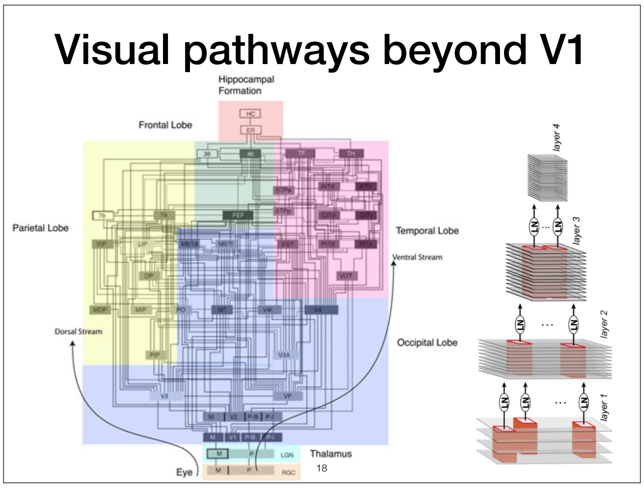
-In V1, different features are processed in intermixed columns, and something similar happens in the next areas, V2 and V3.
-After V3, form and motion information are often processed separately in different areas
-One of these pathways specialises in motion and space processing, while the other is mainly involved in object recognition.
-These are effectively two deep networks, processing information relatively independently but simultaneously to achieve different goals.
-The network for object recognition is well simulated in feedforward artificial deep networks, and we are going to start here.
-The network for space processing is not an obvious target for deep learning in computer vision. It is relatively easy to give computer system good spatial information and make a good spatial model of its environment using a range of sensors and cameras.
-But spatial location is vital to guiding our

attention. Attention is an inherently recurrent process, relying interactions back and forth between earlier and later areas.
-We will see that such recurrent interactions are very important for the brain, and are the cutting edge of developments in artificial deep networks.

Damage to the brain areas in these two processing streams causes very different deficits.

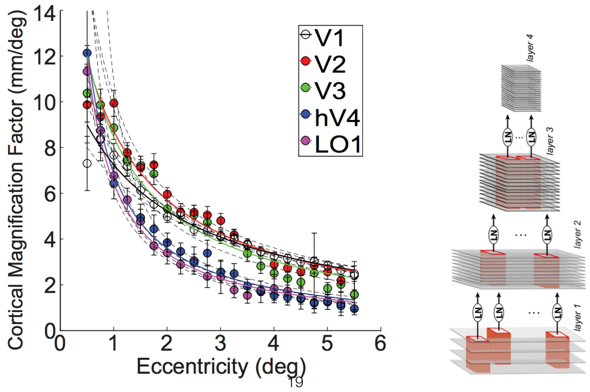


V1 is a visual field map, with a spatial layout.
-Beyond V1, we have a series of further visual field maps, at least 30 over the processing streams
-These may be best understood as layers of deep networks



BUT the hierarchy is not as linear as in an artificial network. After a simple pathway from the eye to V1, lots of areas sample directly from V1, and everything really becomes a web of connections.
-This contrasts sharply with the simple linear hierarchy that has typically been used for artificial networks.
-As we go through more stages, there become more of these areas
-This partially parallels the increasing number of feature maps through an artificial DCNN
-The difference here is that these later brain areas are physically separate, so it is not feasible for a convolutional filter to interact with many brain areas like it can interact with a stack of feature maps.
-Instead, different areas are forming different, largely separated pathways to achieve different tasks, for example object recognition and spatial perception.
-An artificial DCNN, as currently conceptualised, is trained to do a single task. A human can do lots of tasks with the same visual input, and in would likely cause conflicts if a single area had to be trained for many tasks with conflicting demands.

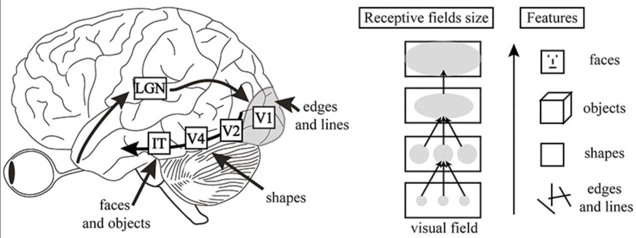
Visual pathways beyond V1



19

Going up this hierarchy (V1-V2-V3-V4-LO1 etc), all of the areas have a larger representation of the central visual field (more millimeters of cortex per degree of retina).
They also become smaller: the area under the curves decreases up the hierarchy.
This resembles the shrinking spatial dimension of an artificial network.

Spatial integration up the hierarchy

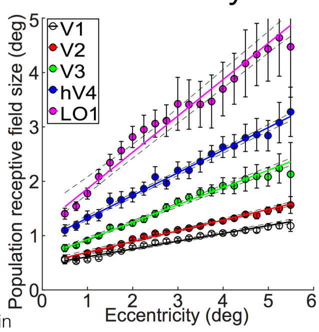


Herzog et al, 2014

20

Through these hierarchical stages, we find responses to increasing complex features over increasingly large areas of space.
-Just like we saw in the retina, these spatial and feature transformations are occurring together: the integrating filters span both the the spatial representation and a range of features, just like the colour filters we saw in the retina.
-The feature transformations are a lot more complex than this, and don't make neat parts like this. We'll look at that later.
-The spatial integration is much

Spatial integration up the hierarchy

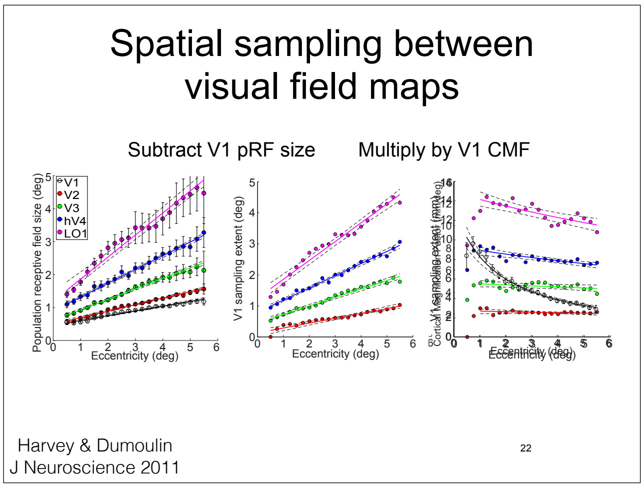


Harvey & Dumoulin
J Neuroscience 2011

21

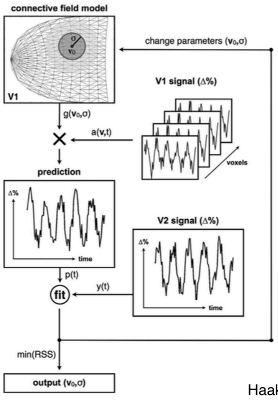
As we already saw, receptive fields get larger moving from the central to the peripheral visual field.
-As we move from early visual areas to mid-level shape processing, we see larger and larger receptive fields: the neurons respond to larger and larger areas of visual space following repeating spatial integration, much like repeatedly passing through convolutional filters.
-Later areas are no longer sampling from the retina or the visual image: their input is always coming through V1.
-Those early visual neurons forming the input already respond to an extensive area of the image,
-So the spatial receptive field of the output cell or artificial neural network unit will reflect the spatial integration already present in the inputs as well as the further

spatial integration between visual areas or network layers.
-Any questions about spatial integration between visual areas or network layers must take this into account. Again we must think how the inputs are transformed, not think in terms of the original image.



So let’s first subtract the receptive field sizes in V1 from those in other areas, reflecting the assumption that these later areas might take their inputs primarily from V1.
-If we subtract out V1’s receptive field size, we see the change in receptive field size from V1, and how this changes from the central visual field to the periphery.
-But this measure is still in terms of the image: how much more of the image is integrated in this step. Of course, these later areas are not sampling the image.
-As we have seen, V1 strongly over-represents the central visual field. This is quantified as the cortical magnification factor: how many millimeters of cortex process each degree of the visual image.
-If we multiply the change in receptive field size by this cortical magnification, we can convert the change in receptive field size, in visual image space, to an extent of spatial integration in cortical millimeters.
-This reveals that the spatial extent of the filter sampling from V1 to V2, V3 and maybe V4 is constant in cortical distance, though not in distance in the visual image.
-The spatial extent of V2’s sampling of V1 is about 2mm, which corresponds closely to the size of a hypercolumn (a piece of cortex containing all feature maps for the same image location), so likely allows V2 to neurons to sample from the full range of V1 feature maps.
-So, an artificial network uses a common spatial extent of convolution filter across the whole feature map.
-But in a biological deep network, the feature map will be biased towards areas that are most useful to us, like the centre of vision. Within that biased representation, there also appears to be a common spatial extent of sampling.

Sampling between cortical areas

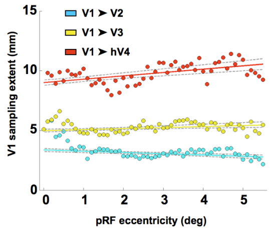


Haak, Winawer, Harvey et al., (2013) *Neuroimage*

We can also ask about this sampling more directly. If we have a group of measurements across the surface of V1, we can summarise a measurement in V2 as the sum of a group of spatially neighbouring V1 signals. If we change the position and spatial extent of the group of V1 recording sites, we get different predictions of each measurement from V2. If we find the prediction that best fits the measured V2 signal, this tells us the location and size of the V1 area that the V2 recording site samples from.

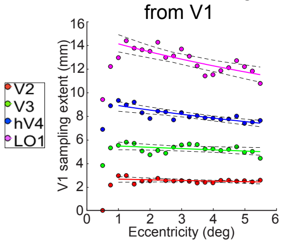
Sampling between cortical areas

Cortical extent of integration from V1



Haak, Winawer, Harvey et al., (2012) *Neuroimage*

Cortical extent of integration from V1



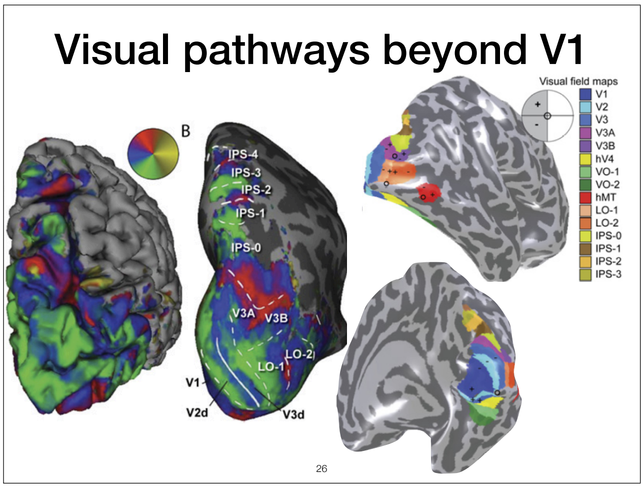
Harvey & Dumoulin (2011) *J Neuroscience*

- Receptive field: Sampling extent of the input image (in visual angle)
- Connective field: Sampling extent of the previous visual field map (in mm)

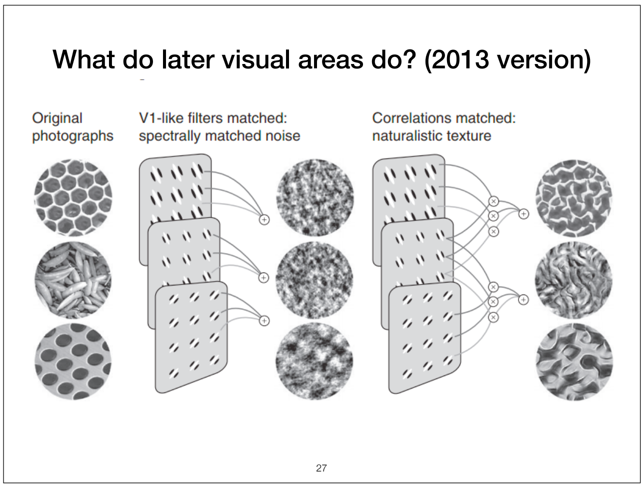
-This also shows that V2, V3 and V4 each sample from a constant cortical extent of V1 throughout the whole visual field map.
-Despite very different approaches, the sampling extents revealed are very similar.
-So this sampling extent is effectively the spatial extent of the filters operating between the feature maps in these different visual field maps.
-In artificial deep networks, this spatial extent of the filters between different layers is often called a ‘receptive field’.
-But this is inaccurate when we think about the brain. A receptive field is a part of the visual image that feeds into a neuron. The part of the previous visual field map that feeds into a neuron is called a ‘connective field’.
-In the brain, these are in very different units, degrees of the retina and millimeters of cortex respectively, so are quite different concepts.
-In artificial networks, they are also different, because the input image is in pixels while the hierarchical layers are in neural network units.

Spatial integration through the visual hierarchy

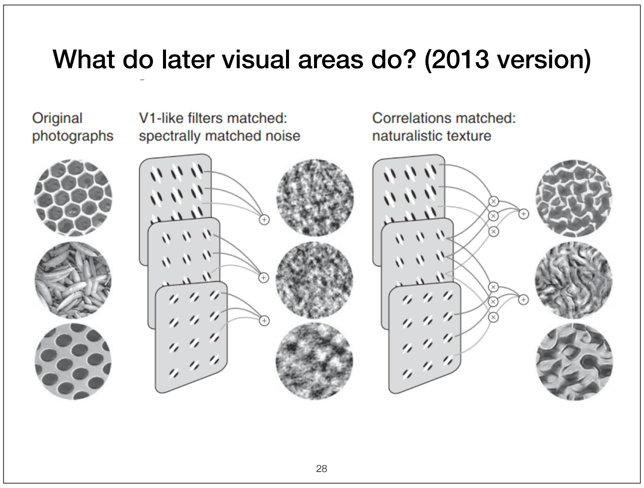
- Visual cortical areas beyond V1 also map the spatial visual field onto the cortical surface
  - Spatial relationships between image locations are maintained
- Multiple branching hierarchies of these visual field maps
  - Performing different tasks
- Main division is into ventral and dorsal streams
  - Focussed in temporal and parietal lobes respectively
  - Involved in object recognition and spatial perception/action planning
- Visual field maps remain biased towards central vision
  - Later visual field maps sample from approximately constant cortical areas of earlier visual field maps, regardless of visual position represented
  - This has some similarity to the fixed size of artificial deep network filters, but the inputs over-represent central vision
  - Neurons, not images



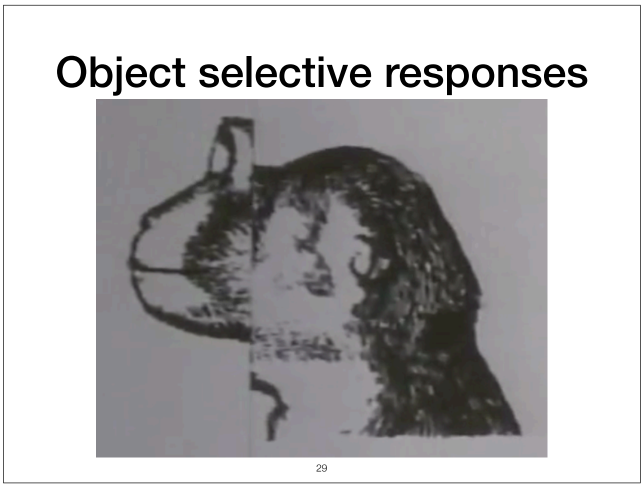
But how are features transformed and integrated?
-The different visual field maps specialise in different things, but beyond a crude description of 'object analysis' and 'spatial analysis', it has been very hard to understand what each area does.
-Humans like to think in terms of an area having a specific function, but we are bad at thinking about a 'function' as being a deep network feature transformation, particularly for the higher layers.
-So humans are bad at thinking in deep network feature transformations, but the brain is very good at doing these feature transformations.'If the brain was simple enough for us to understand, we would be too simple to understand it'



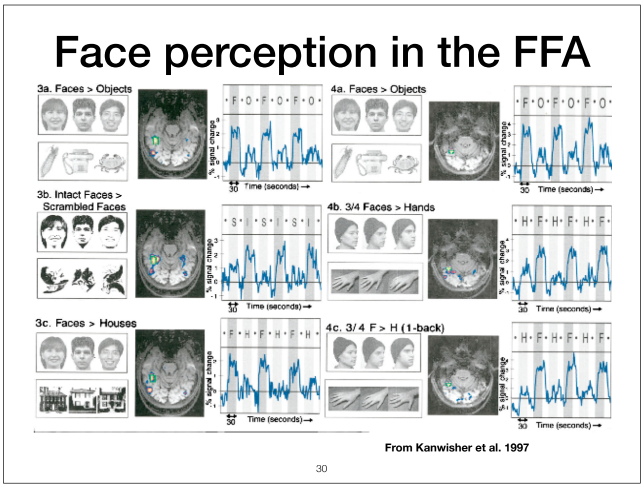
Beyond V1, it has even been hard to figure out what V2 does. Generally, it responds very similarly to V1 when presented with oriented edges.
-Because V1 only responds to the spatial frequencies and orientations in a black-and-white still image, we can make images with the same distribution of spatial frequency and orientation as a natural image. These do not look like natural images, they look like noise. But V1 will respond equally well to both.
-However, V2 responds more strongly to natural images than these noise patterns.
-To make similar responses in V2, the image needs to have a similar pattern of local correlations of orientation as the natural image.
-This appears to be because such patterns of local correlations are common in natural images that have trained the filters linking V1 to V2 i.e. it responds when inputs have the correlations that are common in the real world. By V2, if it fires together, it wires together.



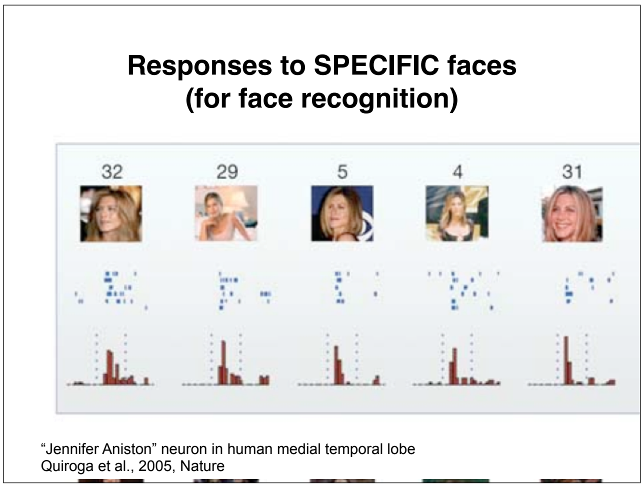
-Orientation-selective responses in V1 were first discovered in 1959. It took until 2013 to reveal how these were transformed by V2. Before 2013, researchers tried to explain V2's responses with reference to features in the input image, rather than patterns in V1's output.
-This highlights the limitations of human thinking about feature transformations: we have a bad habit of thinking in terms of the input image, rather than the pattern of activity in the previous layer.
-Beyond V2, we still don't have a good feeling for what drives responses, but we now understand it is likely to be a feature transformation from the outputs of previous network layers.
-We also understand that this mid-level representation is most likely optimised to allow subsequent transformations to support object recognition. Mid-level representations are certainly not optimised to make sense to human experimenters, as much as we might like that.
-It becomes very difficult for experimenters to think about neural representations and transformations beyond this.
-If we want to make a hypothesis about what later levels are doing computationally, the answer is likely to be in deep network terms.
-So deep networks become a very useful tool for guiding our hypotheses and interpreting experimental results.



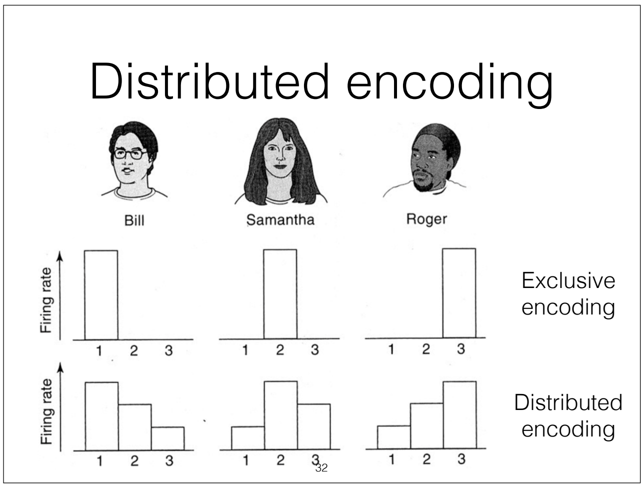
Much further up the processing hierarchy, we eventually find object-selective responses, as we saw in our previous classes.



Here we see human face-selective cortex with fMRI.
It responds more to faces than various other object types



Looking at a whole brain area will group responses to ALL faces.
-But within this area, there are even cells that respond more strongly to specific faces, importantly regardless of the image used and its activation of the retina.
-This neuron responds strongly to Jennifer Aniston, from any angle, size and position.
-It responds less to Julia Roberts, even where she is at a similar angle, size and position as Jennifer Aniston.
-So here the response is not driven by what the image looks



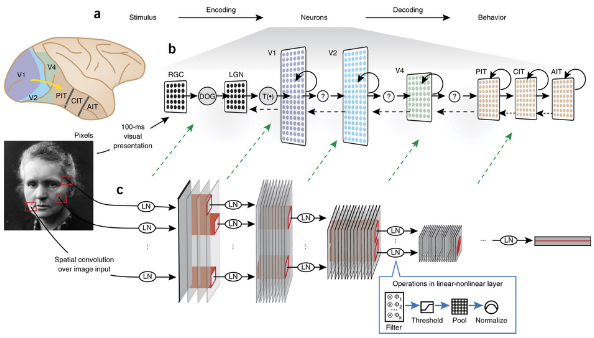
But, given the complex nature of feature map representations, perhaps we would not expect a single neuron to respond so cleanly.
-There is no need for information about a single object to be held by a single neuron
-Perhaps the pattern of activity across a larger group of neurons is used to represent the middle layers, and even the higher layers
-Then, the object identity is not straightforwardly reflected in the activity of a single neuron, but the pattern of activity in a larger population of neurons.
-Again in this way, this mid-level representation appears to be optimised to allow subsequent transformations to support object recognition, not to make sense to human experimenters.

-Exclusive coding would be easier to understand, but probably not provide an optimal input to later stages.
- For example, the last layer of an artificial DCNN for object recognition is fully-connected.
-So it makes a decision based on the pattern of responses across all of its top-layer units.
-In a computation like this, a distributed pattern will allow the right decision just as easily as the response of a single cell.

Advantages of distributed encoding

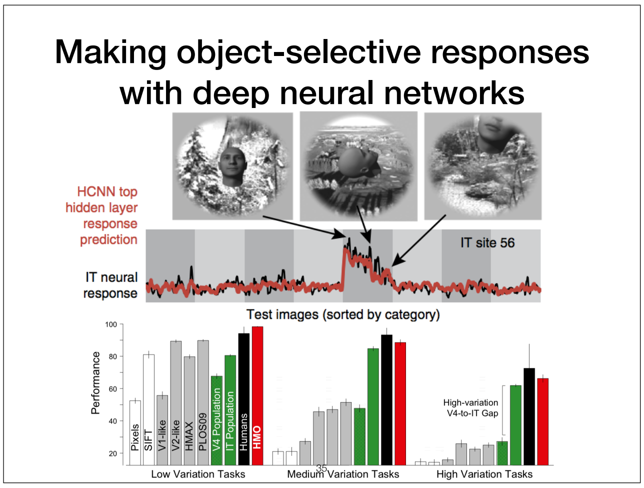
- Allows some cell death without representation failing (graceful degradation)
  - Most of the pattern remains
- Allows new patterns to be stored without new cells
  - New objects can be stored
  - A fixed group of cells can store a variable number of objects
- Consistent with measured cell properties
  - Rarely all-or-nothing responses
- Disadvantage: Harder for humans to understand

Making object-selective responses with deep neural networks



Although we don't have a good feeling for what is happening in the middle layers, we believe that they are using deep network structure to transform visual image representations to object representations.
-If we compare the brain's object recognition network to a deep network, we see that there are many similarities in the spatial representation of features, and the spatial sampling between layers.
-Early layers do simple edge detections.
-Later layers just form associations between the output of earlier layers, based on previous experience of correlated response patterns.
-We understand the processing step at each level, just drawing associations in the activity of previous levels
-But it's hard to intuitively understand

how this will work over many levels, which may be why it has taken us so long to understand.
-Despite that, we can simulate this process and see how the simulation performs.



Responses of later network layers closely resemble responses of face-selective cells.
-This is our current best theory of how object-selective responses arise.
-Importantly, we see a very similar response to faces even if the images vary greatly in position, size and viewing angle.
-In image sets with low variation of position, size and viewing angle, many simple computational models have high object recognition performance, comparable to human object classification abilities. V1-like models and V2-like models do well here.
-Once we introduce more variation in position, size and viewing angle, the population of IT neurons does much better than a population of V4 neurons. And a deep network (HMO, hierarchical modular organisation) does much better than the simple models in gray. Indeed, humans, IT neurons, and deep network models all do well here.

Face processing is also an exciting recent application of artificial DCNNs.

'Deepfakes' are videos where a DCNN is used to map one person's face onto another. The result is a very convincing video of the target face identity following the actions of the source face.

The deepfake process involves first showing the network a large training set of videos of the target face. The network then maps the features of the face and their movements, and matches those to the features of the source actor.

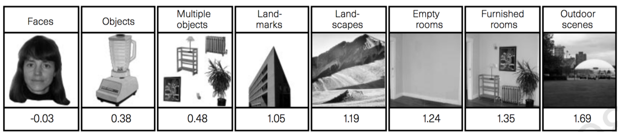
In this example, Freddie Mercury's face is mapped onto actor Remi Malek, who recently played Freddie in a movie using only a fake moustache and teeth.

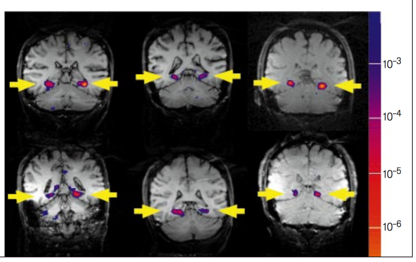
It helps that Remi already looks a little like Freddie. Everything but the face remains unchanged, and these are Remi's ears and hair.

Feature transformations through the visual hierarchy

- TTransformations find commonly-seen patterns in activity of earlier layers
  - Have been difficult for human experimenters to recognise
- Later stages are likely doing the same computation, but from more abstracted inputs (i.e. the outputs of earlier transformations)
  - But it’s really hard to think about these representations and transformations
  - So we simulate them with artificial DCNNs
- Later in the ventral stream, face-selective neurons are found
  - Artificial DCNN simulations produce impressively similar results
  - Artificial DCNNs can convincingly manipulate facial identity

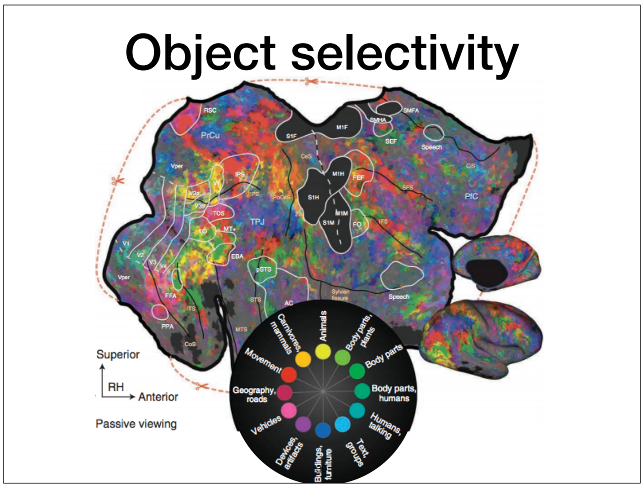
Responses to places



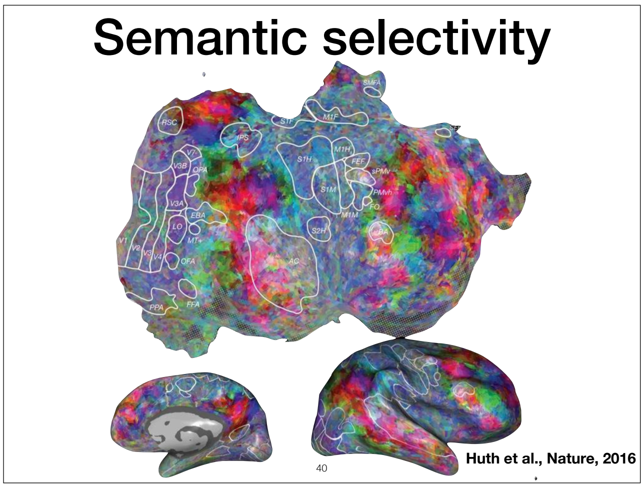


Epstein & Kanwisher, Nature, 2008

But faces are not the only type of objects that produce responses in specific brain areas
–If we show subjects in an MRI scanner pictures of objects, faces, and places, we also find an area that responds specifically to places.
–This has almost no response to faces, some response to objects, and a stronger response to places.
–Again, the images of places vary considerably, but all are clearly places
–The images of landmarks and objects look relatively similar, but the responses they produce are very different.

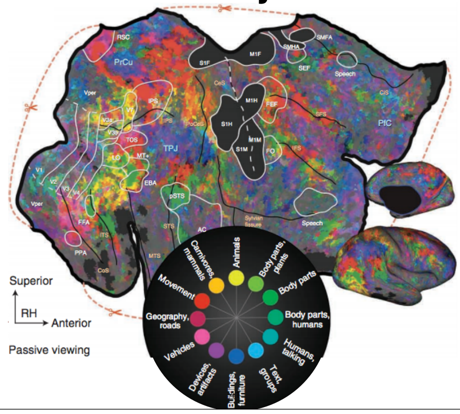


-Here, experimenters labelled all objects in natural movies, then shown these movies to a brain.
-By correlating the responses with the content of labelled movies, they have determined the object preferences of fMRI recording sites in a less biased way
UNFOLDED BRAIN, FFA, PPA
-We see a lot of brain areas responding to various object types, labelled with different colors
-So there are object-selective areas for a large range of object types.



More recently, the same group has revealed a network of areas responding to different types of semantic content in tagged narrative speech and reading.
-This is particularly important because we can't investigate linguistics well in animal models of the brain.
-But also, this is interesting because, although we have little idea how the brain processes language, we see that it reaches very similar results to processing visual objects (although in very different areas).
-This implies deep learning mechanisms are likely to be involved in language comprehension.
-This paper is on your reading list

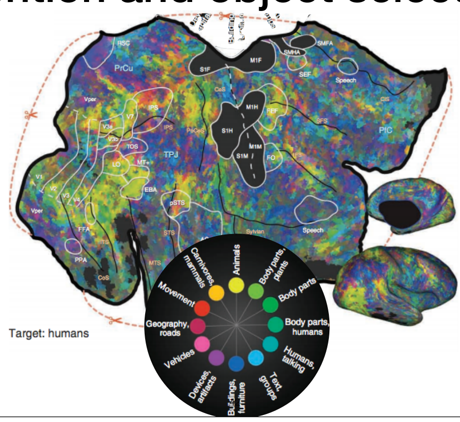
Attention and object selectivity



When mapping these visual object-selective responses, the subjects were just passively watching the movies

---

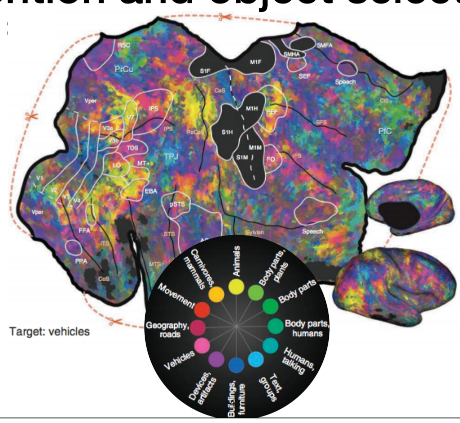
Attention and object selectivity



When subjects have a task to press a button when the see a human, they have to pay attention to humans. Recording sites throughout the brain change their object selectivity, and start responding more strongly to humans and similar objects, in blue-green colours

---

Attention and object selectivity



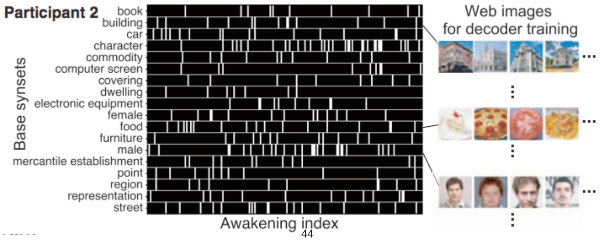
And when they are asked to respond to vehicles instead, recording sites start responding more to man-made objects like vehicles

Therefore, object selectivity throughout the brain depends strongly on what task we are doing. A face-selective area can become a car-selective area if given a car identification task.

Dreams and object recognition

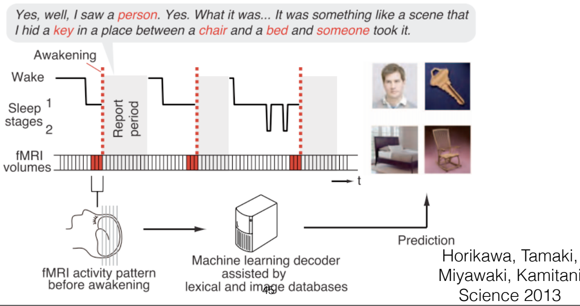
Horikawa, Tamaki, Miyawaki, Kamitani Science 2013

- If we show awake humans in fMRI scanners categorised visual images, we can associate a pattern of brain activity with each category



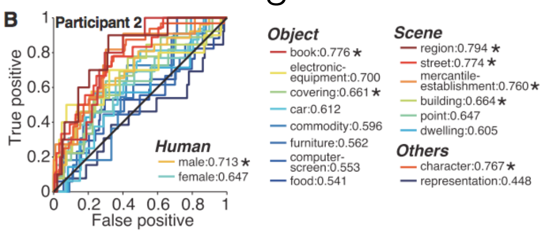
Dreams and object recognition

- We can then wake them up when dreaming and ask what they were dreaming about



Horikawa, Tamaki, Miyawaki, Kamitani Science 2013

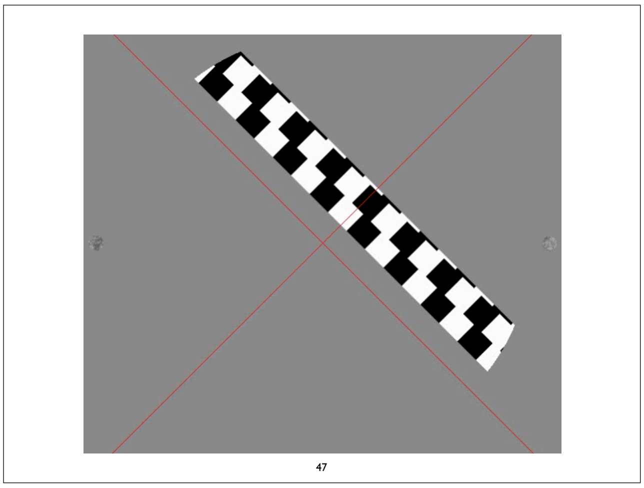
Dreams and object recognition



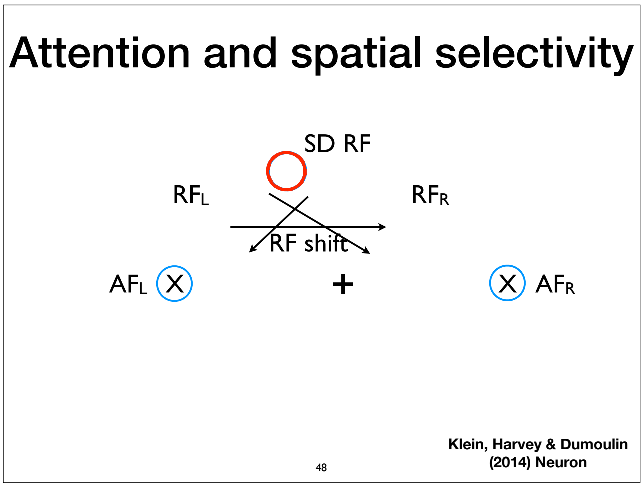
- And we can predict, better than by chance, what they will say by examining their brain activity while dreaming

So this shows that the brain's representation of objects in dreams is similar to the representation of objects we see
Some of these objects have higher scores, meaning they produce more specific patterns of brain activity in more distinct areas
These include people (which have faces), scenes (places) and books (words)
Other types of object (food, furniture) give less specific responses, and cannot be easily distinguished from other objects.
Chance performance is 0.5 here.

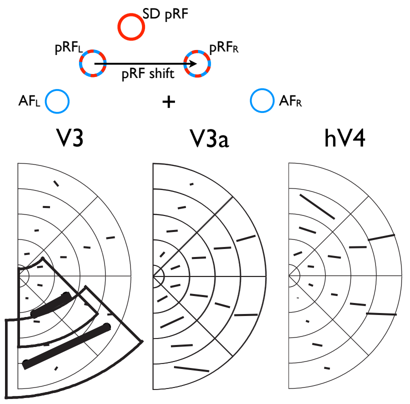
So there do not seem to be specific locations responding to those objects (food, furniture).



Similarly, attending to a specific spatial location attracts spatial receptive fields towards that location. Here, we can use the responses to this moving bar to map out the spatial receptive fields of fMRI recording sites throughout the brain. While doing this, we can get subjects to do a very difficult task at one of two spatial locations, the little patches on the left and right. These are intentionally hard to see, so you really need to pay attention to see them when looking at the cross.



If we attend to left target, receptive fields are drawn towards that target
If we attend to the right, receptive fields are drawn to the right
We can then compare these positions to see how attention affects receptive field positions



All areas show the receptive field shifts

Klein, Harvey & Dumoulin (2014) Neuron

49

Here we see the receptive field positions when attending left and right, with a line joining them

*effect size exaggerated

50

This reallocation of the visual position representation has the effect of zooming in on attended areas.

Object-selectivity, imagination and attention

- Responses to many classes of object
  - Faces, places, words and tools are commonly examined
- Similar responses recently found for semantic content in language
  - Suggests similar processes are involved
- Responses can be driven by imagined content too
  - Gives similar responses to seen content
  - All the way back to the early image representation in V1
- Responses are drawn towards attended content
  - Object responses drawn towards attended object
  - Spatial responses drawn to attended locations

51

AT END:
None of this can happen in the networks we have seen so far.
These take an input, transform it and give an output.
There is no way that imagined content or attended content can affect this process.
Imagining an object will start by activating a high level object representation, which must then be fed back to the earlier representation of the visual image.
Similarly, attention is thought to be driven by higher levels, where goals and decisions are represented, then fed back to earlier stages.

So next class we are going to focus on how such recurrent processes are implemented, which reveals the value of recurrent neural networks for both data science and simulating biological systems

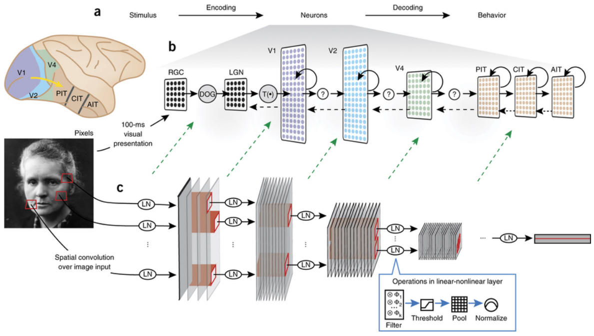
Now read this:

Kay KN, Naselaris T, Prenger RJ, Gallant JL (2008) Identifying natural images from human brain activity. Nature, 452 (7185): 352-355.

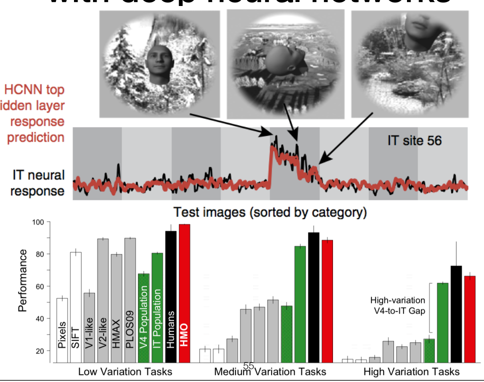
Now read this:

Yamins, D. L., H. Hong, C. F. Cadieu, E. A. Solomon, D. Seibert and J. J. DiCarlo (2014). "Performance-optimized hierarchical models predict neural responses in higher visual cortex." PNAS 111(23): 8619-8624.

Making object-selective responses with deep neural networks



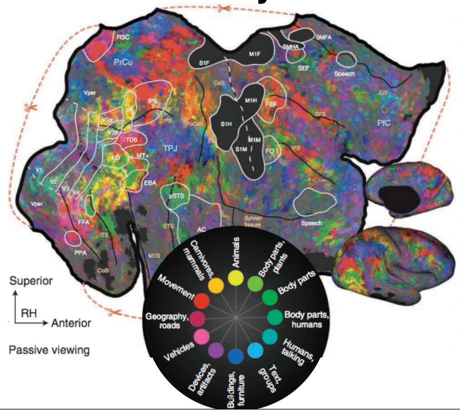
Making object-selective responses with deep neural networks



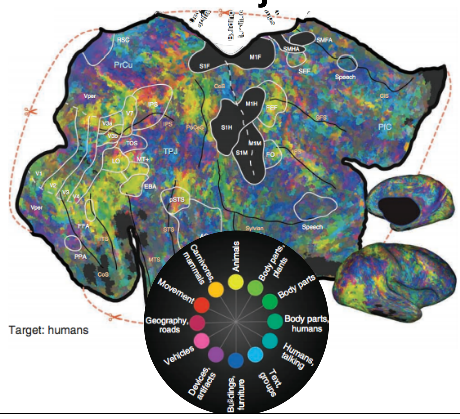
Now read this:

Çukur T, Nishimoto S, Huth AG, Gallant JL (2013) Attention during natural vision warps semantic representation across the human brain. Nature Neuroscience, 16: 763-770

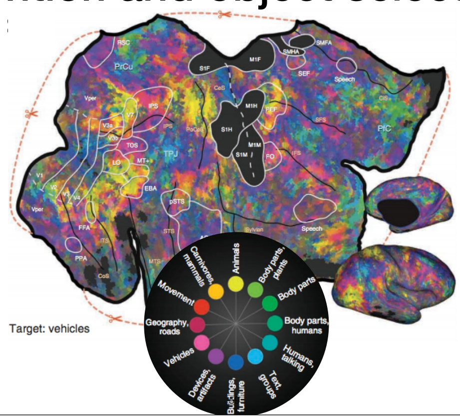
Attention and object selectivity



Attention and object selectivity



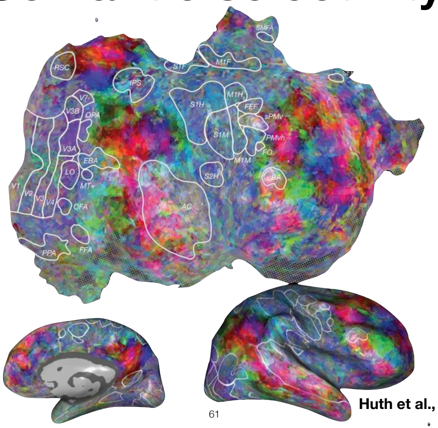
Attention and object selectivity



Now read this:

Huth AG, de Heer WA, Griffiths TL, Theunissen FE, Gallant JL (2016) Natural speech reveals the semantic maps that tile human cerebral cortex. Nature. 532(7600):453-8

Semantic selectivity



Huth et al., Nature, 2016