Week 5: fMRI – blood-oxygenated dependent (BOLD) signal is an indirect measure of neural activity since neural activity is accompanied by a local over-supply in oxygenated blood which is diamagnetic and enhances signal.

Statistical parametric mapping is used to fit a general linear model to brain activity at each measurement point (voxel) in each condition. Then there is a comparison of model fits between the 2 conditions to create a statistical map that indicates BOLD signal in voxels in condition A that were **statistically significantly** larger than condition B.

Kanwisher (1997) – fusiform face area more active to faces and parahippocampal place area more active to places = there is a 'face' region and 'place' region in the brain. But impossible to have a module for every object in the brain? We learn more about brain than 'face processing.'

Reverse inference problem – deductively invalid inference in that the engagement of a particular cognitive process is inferred from activation of a particular brain region

1. In this present study, when task A = brain region Z is active.
2. In other studies, brain region Z is active to cognitive process X
3. Therefore, in our study, activity in brain region Z occurs due to cognitive process X engaged in task A

Problem 1 – brain region Z may be active for many tasks (activation not exclusive)
Problem 2 – experimental setup fails to manipulate/operationalise the latent cognitive process – meaning we cannot always make valid inferences of brain regions for cognitive functions from past studies

'Multi-Demand' network (Duncan, 2013) – proportions of neurons recruited across the brain that differ by **demand** and not function for all higher-order cognitive processes = no specialised regions. Flexible neural properties that dynamically adapt to code specific cognitive processes/content of current task.

'Read out' or 'decode' content of cognitive processes from brain activity. Easy classification problem – voxel in FFA peak to face stimuli, and voxel in PPA peak to place stimuli. Perhaps, based on the firing of a single measurement point (**voxel**) – we can decode stimuli people are seeing? The highest resolution of the brain is a voxel (1 x 1 x 1 mm) which is packed with millions of neurons and we assume these are encoding for all objects we see.

Cat visual cortex – neighbouring clusters of neurons with similar preferences/biases to line orientations. In one voxel, majority of neurons prefer vertical. If you show a vertical line = this 'vertical' voxel will fire more than a 'horizontal' voxel with majority of neurons that prefer horizontal. Voxels with preferences mapped on V1 = **stable and reproducible pattern**. We don't need to rely on average BOLD signals – we use small biases in voxels and use these meaningful patterns to infer the object/cognitive process/content that people are representing/processing. This consistent **pattern** emerges across the entire cortex (not specific region).

Haxby (2001) – suggested no specialised 'object' regions in the brain. Rather, the brain represents objects as **distributed patterns**. Correlations of distributed representation patterns were higher for within-category objects (face vs face) than between-category objects (face vs. cat). This pattern held when maximally responsive voxels for faces and places were removed. Concluded FFA and PPA may play a role (since very active) but the brain represents objects as a distributed code and not modular code.

Multivariate pattern analysis (MVPA) – predict the content of cognitive processes from brain activity to learn more about cognition through neuroimaging. We can train machine learning classifiers to learn similarities and distinguish between distributed pattern representations of objects/stimuli. If this pattern was just 2 voxels – chair is represented by greater activation of voxel 1 than voxel 2, and piano is represented by greater activation of voxel 2 than voxel 1. The classifier can draw a hyperplane to separate these data points in multidimensional space. We use 90% data to train classifier and 10% data to test classifier. **'Classification accuracy'** = % of time classifier correctly predicts the cognitive process/content from information in brain activity pattern. >50% suggests performance greater than chance (statistically significant prediction) and <50% suggests prediction was at chance (guessing cognitive process from brain activity pattern).

MVPA predicts the content of cognitive processes from brain activity. It investigates the **similarity** of distributed activation patterns for different mental processes. We want to investigate whether the classifier can predict cognitive processes/content from brain activity patterns. Hypothesis-free **"Searchlight"** approach allows us to use the classifier to predict cognitive processes/content from brain activity patterns at **each voxel** at a time. Each prediction analysis at each voxel gives rise to a classification accuracy for every voxel. We map these classification accuracies to clusters of voxels to create a brain map of **information content** (not activation).

Voxel – smallest unit of measurement of anatomical volume. We take one voxel at a time out of the cluster and build a **pattern vector**. Grayscale = numbers = **spatial pattern**. We give this to a classifier to see if it can predict the cognitive process/content from the brain activity pattern or not.

4 basic steps in MVPA:

1. **Feature selection** – deciding which voxels will be included in classification analysis (unless searchlight approach)
2. **Pattern assembly** – sorting data into discrete 'brain patterns' corresponding to pattern of activity across voxels for an experimental condition
3. **Classifier training** – feed a subset of fMRI data pattern (training data = 90%) into a classifier to learn the function (hyperplane) that maps between voxel activity patterns and experimental conditions
4. **Generalisation testing** – feed new test data (10%) into classifier to see if classifier can correctly determine the experimental condition associated with that response pattern (>50% = accurately predict)

Haynes (2007) – Decoding hidden intentions of adding or subtracting numbers. Participants freely required to hold the intention (add or subtract) in mind during variable delay phase. During this phase, brain responses recorded by fMRI. Applied MVPA to patterns of brain responses under 2 possible intentions (add or subtract). MVPA could accurately decode intent (add or subtract) with highest decoding accuracy from medial PFC during anticipation phase. MVPA could decode intent from posterior PFC during execution phase.

Haynes & Rees (2005) – Decode line orientation of invisible stimuli. Showed that voxels in V1 show weak but reliable line orientation preferences. Using multivariate pattern recognition, they accumulated this weak information across many voxels to yield a direct measure of orientation-selective processing. They used a visual masking technique of a stimulus comprised of a line orientation alternated by a mask comprised of opposite line orientation, to prevent participants from consciously perceiving line orientation of target object. Found that invisible oriented stimuli were processed in V1 (not V2 or V3). Concludes V1 is not sufficient for consciousness.

Haynes & Rees (2006) – Decode changes in conscious visual perception. When 2 stimuli (red and blue) were presented to each eye separately, they cannot be perceptually fused. Instead, conscious perception alternates between stimuli. Participants pressed one of two buttons to indicate which of the 2 stimuli they were seeing. Distributed fMRI response patterns recorded concurrently showed some regions with higher signals during perception of red stimuli and other regions with higher signals during perception of blue stimuli. A pattern classifier was trained to identify phases of red vs. blue dominance based on distributed brain response patterns. By applying trained classifier to test data, it was possible to decode with high accuracy which stimulus the participant was currently consciously aware of i.e., reliably track changes in conscious perception. Shows V1 represents non-changing visual stimuli.

Stokes (2009) – Decode imaginary visual experiences. Participants i) viewed and ii) imagined letters 'X' and 'O'. MVPA was applied to fMRI patterns to show classifier could distinguish between activation patterns in **anterior and posterior lateral occipital complex** to the 2 letters 'X' and 'O' in both **stimulus-driven perception and visual imagery**. Cross-generalisation between activation patterns in visual cortex underlying perception and imagery – suggest that top-down (imagination) and stimulus-driven mechanisms activate shared neural representations within high-level visual cortex.

Horikawa (2013) – Decode content of dreams. Participants fell asleep in the fMRI and were woken up during stage 1 & 2 sleep and were asked to report objects in their dreams. These objects were extracted from an image database. Participants then viewed those images in the fMRI again and this was given to the classifier as training data. fMRI data during sleep was used as test data to see if classifier could decode objects from this data which it could. Suggests common lower visual cortex (V1, V2, & V3) and higher-order visual cortex (temporal regions) involved in both visual perception and visual experiences during sleep.

Soon (2008) – predict free motor decisions. Participants in fMRI could freely decide when to press a L or R button and required to remember letter on screen at time of conscious decision. Researchers used letter as a marker to look at neural pattern leading up to it – to see how much information each brain region contained about outcome of motor decision. Classifiers were trained to predict the outcome of a participants' motor decision by recognising specific brain patterns associated with each choice. Two brain regions that encoded with high accuracy whether the participant was about to choose L or R prior to conscious decision from **anterior medial prefrontal cortex (frontopolar cortex)** and **medial parietal cortex (precuneus to posterior cingulate cortex)** up to 10 seconds before they were aware of conscious decision (haemodynamic delay of BOLD taken into account). This suggests that when a participant's decision reached awareness, it had been influenced by unconscious brain activity up to 10 seconds. However, finding may be due to the key press - motor urge?

Soon (2013) – predict abstract decisions. Participants in fMRI freely required to hold intention in mind to either add or subtract and remember letter on screen at moment of conscious decision. They performed the chosen arithmetic task on numbers in next 2 frames and selected answer on subsequent frame. Researchers used letter as a clock to look at neural pattern leading up to it. In different brain regions, independent classifiers were trained to distinguish between spatial patterns of brain activity related to the two intentions. The accuracy with which a classifier could predict the specific choice revealed whether a particular brain region contained information related to the content of the intention at a specific point in time. Found that the **medial prefrontal cortex (medial frontopolar region)** and **parietal cortex (region between precuneus and posterior cingulate region**) began to encode the outcome of the upcoming decision up to 7 seconds before participant was aware of decision (taking into account hemodynamic delay). At some point – a pattern starts to build and get stronger and crosses a threshold to code for one of the decisions. We are probably picking up the evolution of these brain activity patterns towards a decision.