Lab assignment 2 || Cognitive Modeling || Team 16

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Question 1

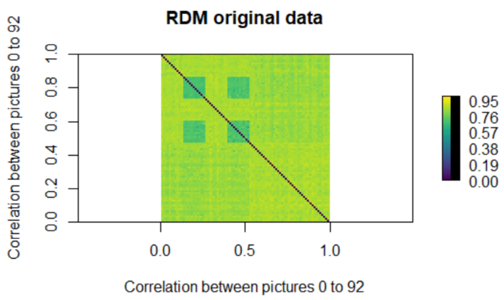
If we take the different voxel activation as an example for these two measures: in the case of the Euclidean distance, the difference between the mean voxel activity between [stimulus 1 and stimulus 2 for each voxel] is calculated. In this case, the absolute difference in scale between different voxels influences the outcome (e.g. a difference between 1 and 1.5 is small (0.5) and a difference between 10 and 15 is large (5)). If the absolute activation of one voxel is much higher than in another voxel, the absolute difference might be higher than in a voxel with generally lower activation, whereas the relative difference might be the same (e.g. a the difference between 1 and 1.5 is proportional to the difference between 10 and 15). Therefore, Euclidean distance can only be used if one wants to look at the absolute difference in measures between two data points. The Pearson is invariant to adding constants, since the means are subtracted out by the construction of the formula. The correlation coefficient therefore takes the relative distance between two points into account. The absolute distance is therefore irrelevant. This is useful in the model we are coding at the moment, since only the relative activation difference between voxels is needed, not the absolute difference.

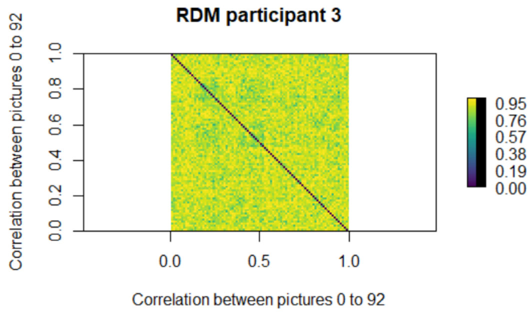
Therefore, correlation metrics is excellent when you want to measure distance between such objects as the expression profile of genes (SNIP significance level in GWAS) that can attain extremely high significance values, hence a wide range of significance values (e.g. p-values from 10^{-2} to 10^{-15}). fMRI significance activation is similar in that perspective, since voxel activation can also have a very broad range of significance value (up to 10^{-10} or more).

Euclidean distance should be used when interested in the actual difference in values of attributes. For instance when optimizing infrastructure construction between two points (cities) it might be important to know the absolute value of the distance between the cities to take into account for cost/resource calculation of the project.

Question 2

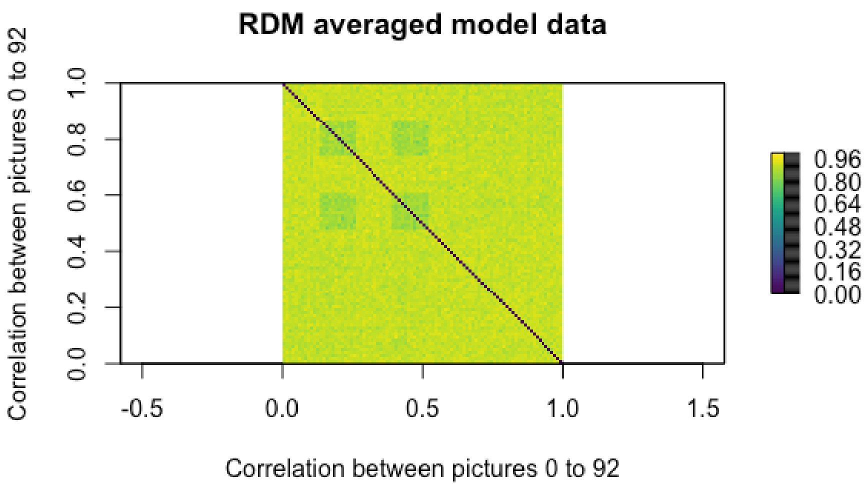
The original RDM shows a relatively smooth and clean pattern with some pictures being more similar to each other (the rectangles) than the rest, with the rest showing much weaker similarities between participant reactions to the pictures shown. This is true for the three sets of images shown in the top left corner. Slightly higher similarity also occurs in the large square in the bottom left corner, although the contrast is not as big. Looking at the data we used in question four, the initial guess is that this is because of the animate-inanimate difference. The diagonal shows the 0-dissimilarity of every image with itself. The mirror image over the diagonal in this case means that the same data is represented twice, once on each side of the diagonal. Participant 3 has some noise added and thus the similarity pattern is almost not visible anymore. Overall, the dissimilarity gets higher (more yellow), because the chance that with random noise two similar ones get dissimilar is high, while the chance that two dissimilar ones get similar is slim. So any noise will not only distort the pattern, but also increase the overall dissimilarity.



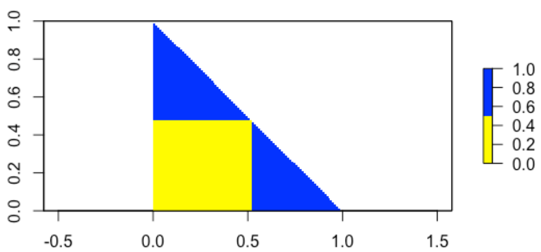


Question 3

The "average subject" shows the groups of pictures that are more clear to each other more clearly than the single model subject. This makes sense, since all model data contains the original data plus slight deviation. This deviation can be added in either direction (the original value plus or minus the deviation). Therefore, averaging the data is likely to get closer to the original. The average is also more dissimilar, since all model data is more dissimilar, as described in question two.



Question 4



The animate object similarity mask (i.e. all values in V1 with the same values) the data is tested with. Blue indicates correlations for pictures with the same state of animacy and yellow indicates pictures with a different state of animacy.

t-test results for the original data ~ the V1 similarity matrix (state of animacy)
t = -230.35
p < 2.2e-16 ≈ 0.00000000000000022

Top blue triangle: both pictures are animate
Bottom blue triangle: both pictures are inanimate
Yellow: the two pictures share different animacy states

If we choose an alpha of 0.05 for significance, which is a regular alpha value, the original data is a relatively good predictor for the animacy effect. The chance (p) that the animacy effect plays no role in the RDM based on the original data is virtually 0. Animacy does surely have an influence on the activity patterns of the 100 voxels that we are looking at.

Question 5

t-test results for model participant 3 ~ the V1 similarity matrix (state of animacy)
t = -57.935
p < 2.2e-16 ≈ 0.00000000000000022

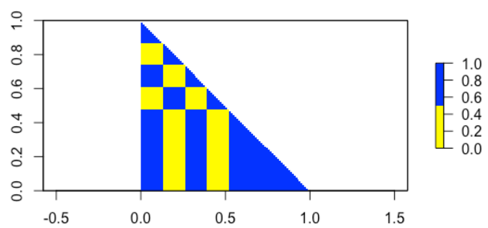
The p-value is still, also with the added noise, basically zero (because it is the lowest number we can get in R). We still find a very significant effect of the same/different state of animacy. The effect is clouded by the noise, therefore the t-value is lower, but it is still very clearly visible.

t-test results for the average subject ~ the V1 similarity matrix (state of animacy)
t = -149.38
p < 2.2e-16 ≈ 0.00000000000000022

The p-value is still virtually 0 and because it is the lowest number we can get in R it is the same as for a single participant, but we would expect it to be lower than the p-value for a single participant, same as the t-value that is higher, because the noise starts to average out with an increasing number of participants.

So the state of animacy is clearly a very important feature that can explain the activation pattern very well.

Question 6



The faces similarity mask (i.e. all values in V6 with the same values) the data is tested with. Blue indicates correlations for pictures with the same state of "faceness" and yellow indicates pictures with a different state of "faceness".

t-test results for the original data ~ the V6 similarity matrix

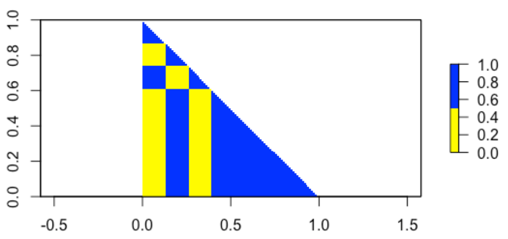
t = 17.112
p < 2.2e-16 ≈ 0.00000000000000022

Blue: both pictures share the same state of faceness
Yellow: both pictures share a different state of faceness.

The “face-ness” does influence the original data’s pattern. The p-value is very low, meaning that it is unlikely that there is no effect of the “face-ness” on the original data. The t-value is lower than for the state of animacy.

Question 7

Faces only for animate objects. Mean of model participants:
t = -22.586
p-value < 2.2e-16 ≈ 0.00000000000000022



Faces only for animate objects. Participant 3:
t= 6.4296
p-value = 1.942e-10 ≈ 0.0000000001942

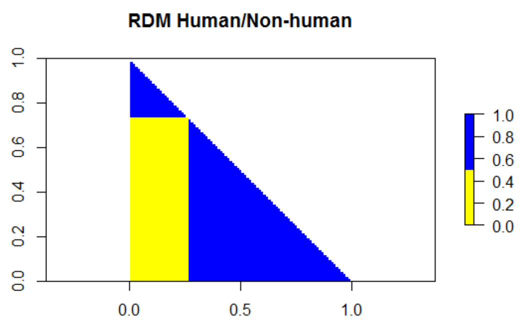
If we compare same state of faceness to different state of non-faceness for all objects we get a higher dissimilarity than when we compare same state of faceness to different state of non-faceness only for animate objects, because faces seem to be more similar to animate objects than to inanimate objects.

- Face-face, house-house vs. face-house
- Face-face, leg-leg vs. face-leg

The t value is lower, since we only compare faces with non-faces (e.g. body parts) in the class of animate objects, instead of including objects that have the same state of inanimacy (an apple) and compare them to all other objects that have a different state of faceness. Here we compare only faces and body parts against animated object that share a different state of faceness. So, excluding inanimate objects, that are inherently different from animated objects (and faces), the t value drops naturally. In addition, one might argue that this reflects a more natural (or reasonable) comparison.

Question 8

Humans. Mean of model participants
t= -12.996
p-value < 2.2e-16 ≈ 0.00000000000000022



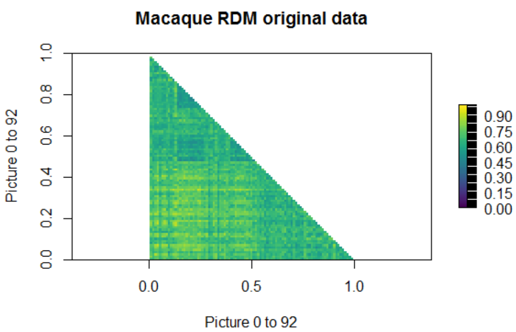
Humans only for animated objects. Mean of model participants
t = -0.45635
p-value = 0.6482

Question 9 & 10

	Df	Sum Sq	Mean Sq	F value	P	n
Animacy	1	95.31	95.31	65586.57	< 2e-16	0.9261
Faceness	1	0.27	0.27	162.48	< 2e-16	0.0516
Interaction	1	0.10	0.10	60.22	1.06e-14	0.0314
Residuals	4182	7.04	0.00			

Question 11

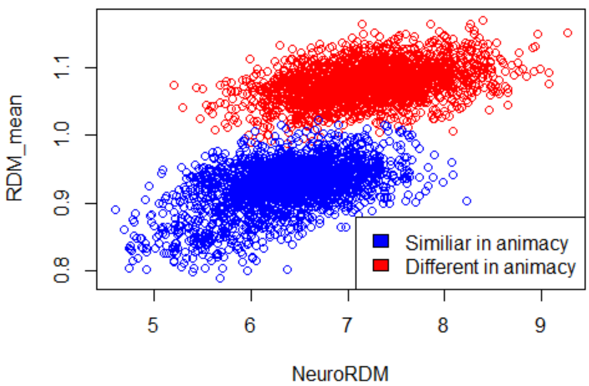
Correlation coefficient (r): 0.67
p-value: < 2.2e-16



The RDMs are significantly correlated. The macaque voxels show the same activity for the different photos as the human voxels. This leads us to believe that conclusions about neural activity for categories in humans are likely to roughly translate to macaques. The low correlation coefficient, however, demonstrates that macaque fRMI data on object representation is very different from our simulated human data on object representation. This might be due to the fact that macaques and human differ significantly in their object representation or it might be due to technical difficulties, ensuring that the human voxels corrensond to the macaque voxels.

Question 12

Correlation coefficient (r): 0.57
p-value < 2.2e-16



The patterns between macaques and humans are more significantly correlated for animate objects than they are for all. This correlation is even higher than in question 11, suggesting that the macaque animacy data relates to the human animacy data. It suggests that the same voxels are likely to be activated when looking at pictures in the animate category. The difference to question 11 might be explained by the fact that macaques are not used to human-made(?) inanimate objects (like cars, tools, infrastructure etc), therefore one could expect a low correlation. However when excluding them the correlation rises significantly, because the monkeys used in the lab are familiar to human face (this might be different for wild monkeys).

Question 13

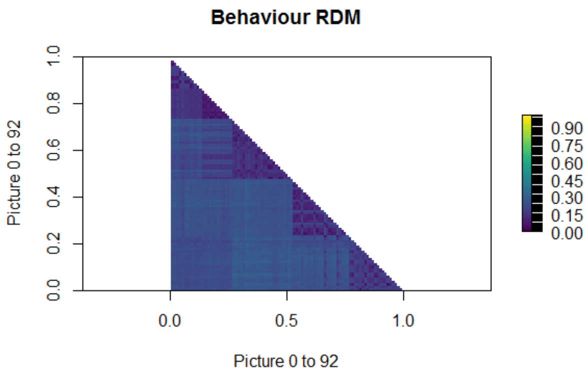
Correlation coefficient (r): 0.31
p-value < 2.2e-16

The correlation is still high, but somewhat less regarding the r-value. This suggests that seeing inanimate objects leads to similar activation in both macaques and humans. As to why the r-value is lower, we have two theories:

1) Faces/animate objects are processed in more detail, since it is of higher importance to be able to distinguish between faces/living things for survival/social life. This could to some degree go for macaques as well. “Animate objects” or “animals” are more likely to be a cause of death for macaques than inanimate objects. This leads to higher dissimilarity, making a higher correlation coefficient possible.
2) Macaques are less exposed to certain inanimate objects than humans. It is, for example, more unlikely that a macaque encounters a car than that a human encounters a car. Therefore, macaques might not be as developed as humans in cases of these objects.

Question 14

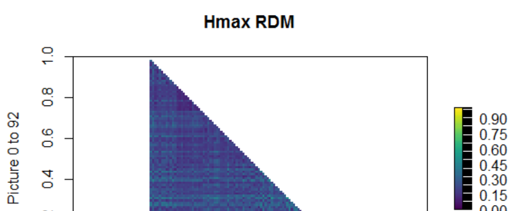
Correlation coefficient (r): 0.61
p-value < 2.2e-16
Correlation coefficient (r): 0.32 (animate only)
p-value < 2.2e-16
Correlation coefficient (r): 0.12 (inanimate only)
p-value = 0.000337



The correlations are all significant, with the animacy p-values and general p-values being more significant than the inanimacy values. This suggests that IT plays a large role in semantic categorization. Given the higher correlation in the animate category, we expect that IT is more involved in the categorization of animate objects (like FFA might be) than in the categories of inanimate objects. Additional brain areas might be used as well (e.g. VWF for letters for example) or involving the full IT in the analysis might be too coarse and high levels of granularity (e.g. lower voxel size) might be necessary to obtain higher correlation values. This explains why humans can make these judgements without giving a full one-to-one correlation in IT.

Question 15

Correlation coefficient (r): 0.13
p-value < 2.2e-16



Correlation coefficient (r): 0.38 (animate only)
p-value < 2.2e-16
Correlation coefficient (r): 0.13 (inanimate only)
p-value = 3.472e-05

Limitations of HMAX are stronger for inanimate objects (less correlation with average subject).
Size effect medium but highly significant. Sources of possible variations :
- Interindividual differences
- Macaques (works better with human face (see 12-13) but not with inanimate man-made objects)
- The data used for RDM_mean only simulates voxel activity instead of using real voxel data
- Hmax is not good at differentiating between animate and inanimate.