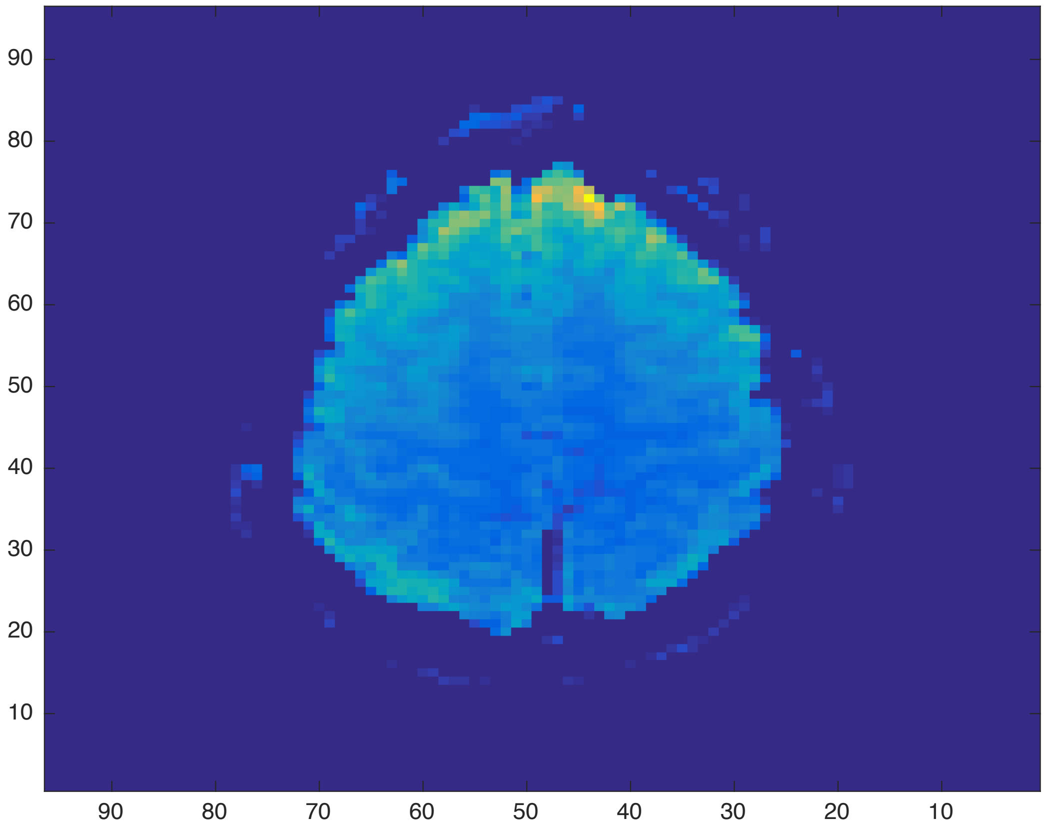
Homework 1 - Model Answer

1. First visualize (for example using imagesc in matlab) the mean T2* image (ANA). Get oriented. Where is the front and the back of the brain? Can you make out the grey matter vs. white matter? (20pts)

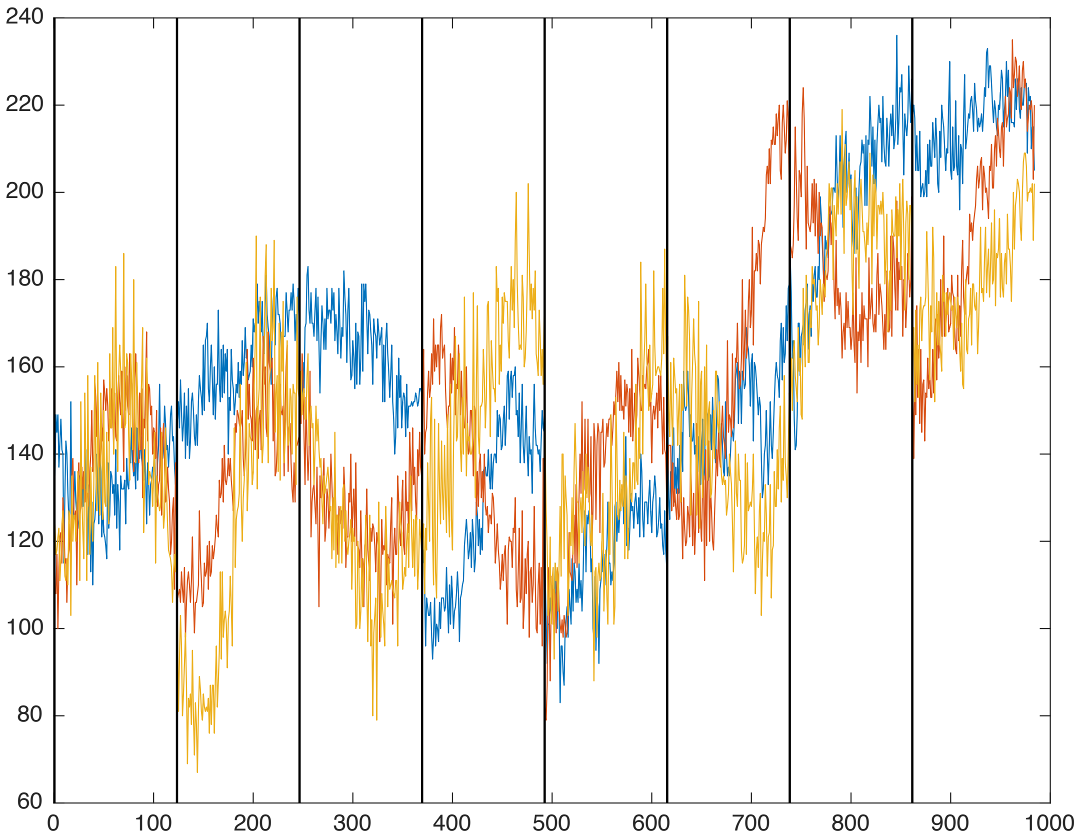
```
load dataset_1
figure(1);
imagesc(ANA)
set(gca,'YDir','normal','XDir','reverse')
```



We are looking at a horizontal slice of the brain. The front of the brain is on top. Gray matter is brighter than white matter, as we are looking at a T2-weighted image of the brain (the contrast would be opposite in a T1-weighted image). The image has a strong non-uniformity that depends only on the coil arrangements (the receiver coils are very close to the forehead).* As I reversed the X-direction (columns), left side of the image is the left side of the brain.

2. Plot some of the time series. Note that the data was acquired in runs of 123 images - and between runs there was a short break. What do you notice about the time series? Think about how these features will influence the modeling of the data. (20pts)

```
figure(2);
Y= reshape(Y,96*96,984)';  % Reshape into a timepoints x voxel
matrix
plot(Y(:,[1869 1958 2056]));         % Plot some voxels
drawline([0.5:123:984]); % Draw lines at boundaries of runs (note:
you may not have that function)
```

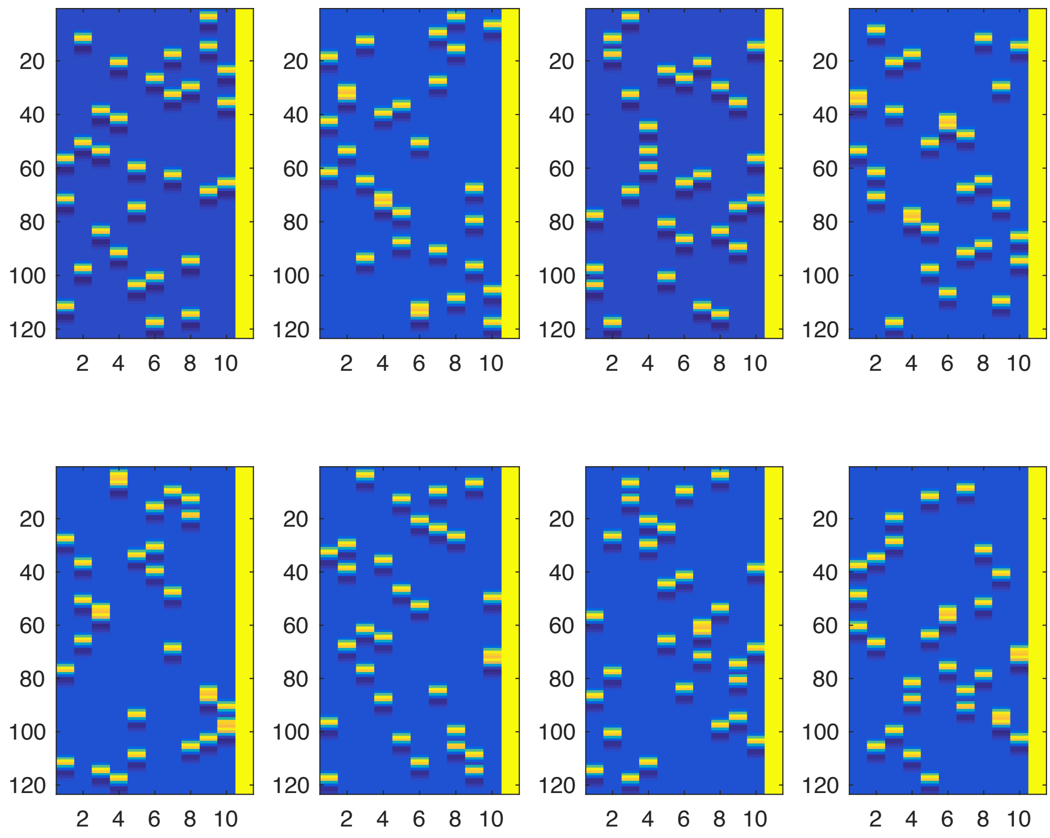


The three voxels plotted show very strong low-frequency fluctuations of the time series. The signal often either increases or decreases within each run - sometimes showing clearly non-linear changes. Additionally, there are jumps in the signal between runs - each run seems to have a separate intercept. Clearly, these features need to be somehow accounted for in the model. In our case we use the run-specific intercept to at least take out the big jumps.

3. For each run, set up a design matrix, consisting of the task related regressors and the intercept. Visualize your design matrix. (20pts)

```
%% 3. Build and visualize the design matrices
for r=1:8
    X=[Xtask(:,:,r) Xintercept(:,:,r)];
```

```
    subplot(2,4,r);
    imagesc(X);
end;
```



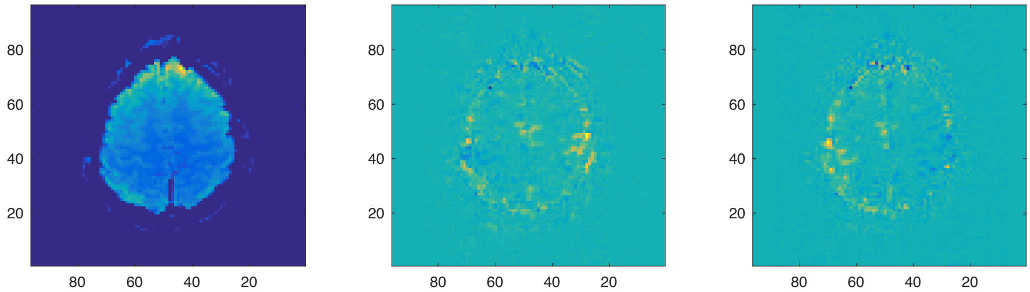
Plotted are the design matrices for each run. Each run looks different - this is because the sequence of trials in each run have been randomized. The first 10 columns mark the occurrence of each trial. The last column is the intercept.

4. Apply Ordinary-least-squares (OLS) estimation to get a regression coefficient for each Voxel. Also calculate the residuals from the regression.

5. Visualize the mean regression coefficient for movements of fingers of the left and right hand (averaged over the 5 fingers and over the 8 runs). Can you see areas activated for each of the hands? (20pts for 4+5)

```
%% 4,5. Use OLS estimation to get the betas
for r=1:8
    X=[Xtask(:,:,r) Xintercept(:,:,r)];
    B(:,:,r)=pinv(X)*Y(run==r,:);
    R(run==r,:) = Y(run==r,:)-X*B(:,:,r);
end;

mB=mean(B,3);                  % Average over runs
LHand = mean(mB(1:5,:),1);    % Average over fingers of the left
hand
```

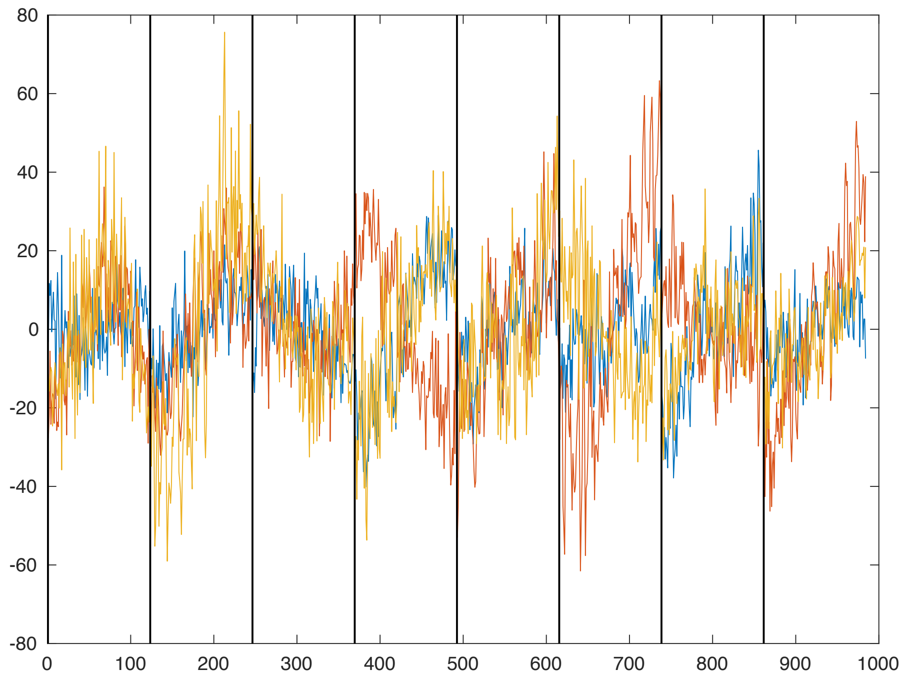
```
RHand = mean(mB(6:10,:),1); % Average over fingers of the right
hand
LHand = reshape(LHand,96,96);
RHand = reshape(RHand,96,96);

figure(4);
subplot(1,3,1);
imagesc(ANA)
set(gca,'YDir','normal','XDir','reverse')

subplot(1,3,2);
imagesc(LHand);
set(gca,'YDir','normal','XDir','reverse');

subplot(1,3,3);
imagesc(RHand);
set(gca,'YDir','normal','XDir','reverse');
```



The first panel shows again anatomical image. The middle panel show activity for left hand movements with activity in right motor cortex and negative signal changes in the left motor cortex. The last panel shows activity for the right hand movements with activity in left motor cortex and suppression on the right. There are also some voxels that are active for both left and right movements.

6. Plot the residuals for the same voxels plotted under 2. What do you notice? How could we improve our linear model? (20pts)

```
figure(5);
plot(R(:,[1869 1958 2056]));         % Plot some voxels
drawline([0.5:123:984]);
```



The residuals from the three voxels plotted above show still a lot of structure. While the different baseline for the different runs is clearly removed through the inclusion of the intercept, there are clear low-frequency drifts within each imaging run. Sometimes these drifts are common across voxels (see run 3), but often different voxel show quite different drift patterns (run 4,6).

To make appropriate inferences, these drifts clearly need to me modelled. This could be done by a) including regressors that model the linear drift or other low-frequency trends in the data b) regressing these drifts out of the data before submitting the data to the general linear model (filtering), or c) taking the temporal autocorrelation of the time series into account when estimating our linear model.