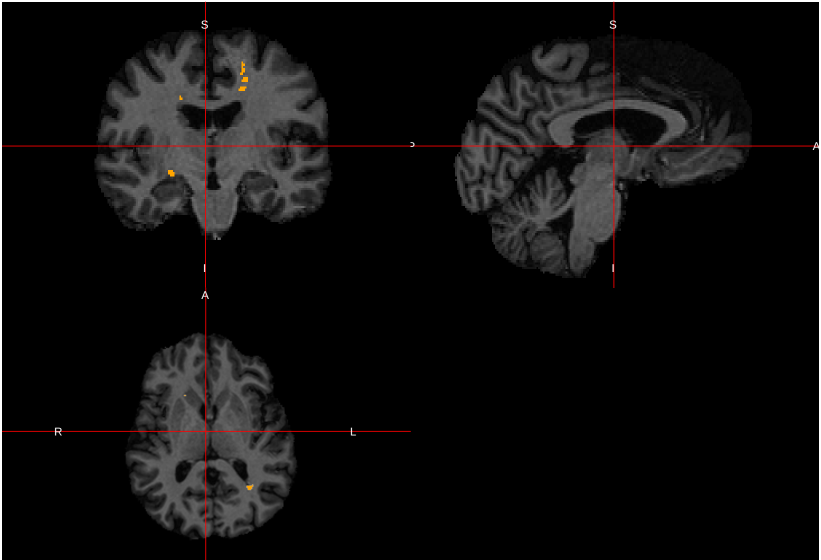
MS Lesion Segmentation

Goals of this tutorial

- Obtaining manual lesion segmentations is often resource intensive, so accurate and efficient methods for automatic segmentation are necessary for scalability and research progress.
- Apply OASIS (Sweeney et al. 2013), an automatic lesion segmentation model, to obtain predicted lesion probability maps.
- Compare the results using the default OASIS settings to those obtained after re-training the model using our data.

Visualization

- Here's the T1 volume for training subject 05 with the 'gold standard' manual lesion segmentation overlayed.



MS Lesion Segmentation with OASIS

- OASIS is Automated Statistical Inference for Segmentation (Sweeney et al. 2013)
- The OASIS algorithm takes FLAIR, T1, T2, and PD images from patients with multiple sclerosis (MS) and produces OASIS probability maps of MS lesion presence, which can be thresholded into a binary lesion segmentation.
- OASIS uses logistic regression of the labels on the images, smoothed versions of the images, and some interaction terms

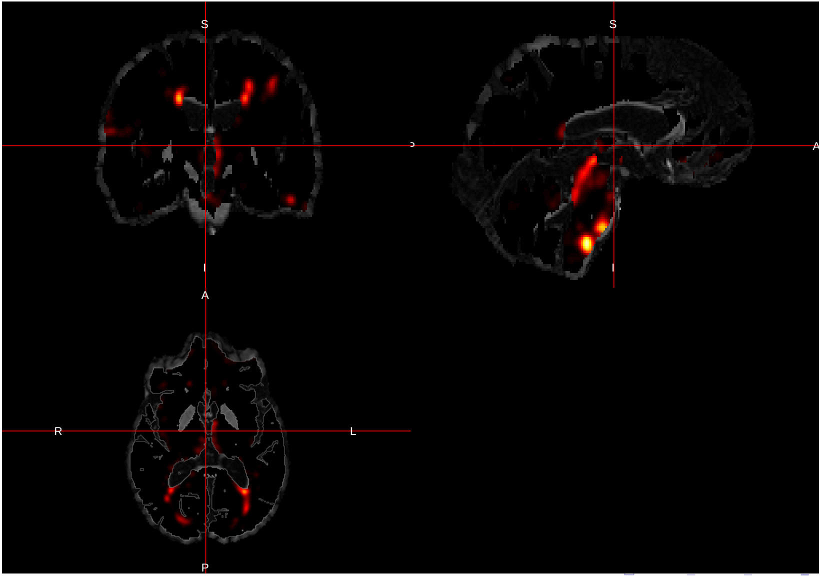
Default OASIS Model

- The OASIS library comes with default parameters that can be used to generate probability maps for new test subjects
- Here we apply the function `oasis_predict` with the default model to obtain OASIS probability maps for the test subjects.

```
default_predict_ts = function(x){
  res = oasis_predict(
      flair=ts_flairs[[x]], t1=ts_t1s[[x]],
      t2=ts_t2s[[x]], pd=ts_pds[[x]],
      brain_mask=ts_masks[[x]],
      preproc=FALSE, normalize=TRUE,
      model=oasis::oasis_model)
  return(res)
}
default_probs_ts = lapply(1:3, default_predict_ts)
```

Vizualization

- Here's the probability map for test subject 01:

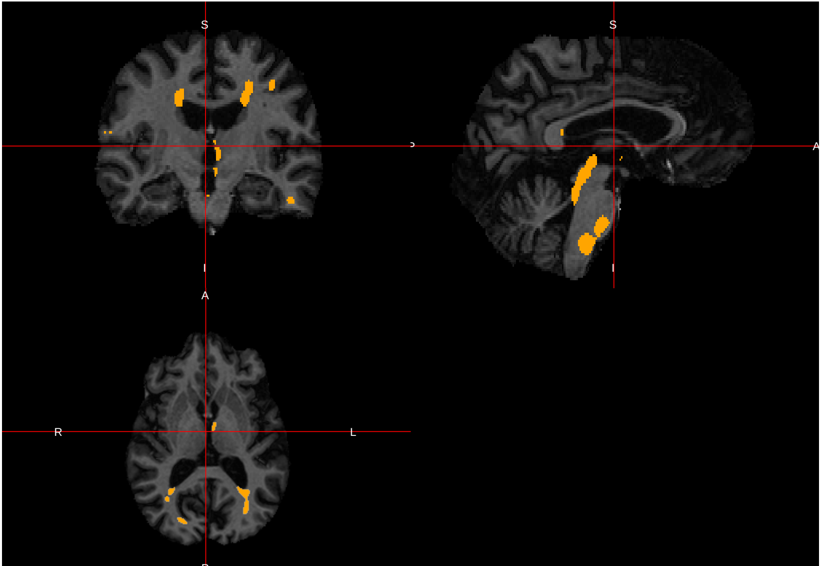


Thresholding

- To get a final estimated segmentation, we must choose a cutoff to binarize the OASIS probability maps.
- The `binary` argument in the `oasis_predict` function is FALSE by default, resulting in the output being the probability map.
- Setting `binary=TRUE` will return the thresholded version, using the input to the `threshold` argument (default $= 0.16$).
- In practice, we might want to use a grid search over thresholds and cross validation to choose the cutoff.

Vizualization

- Here's the binary mask for test subject 01, using the default 0.16 threshold:



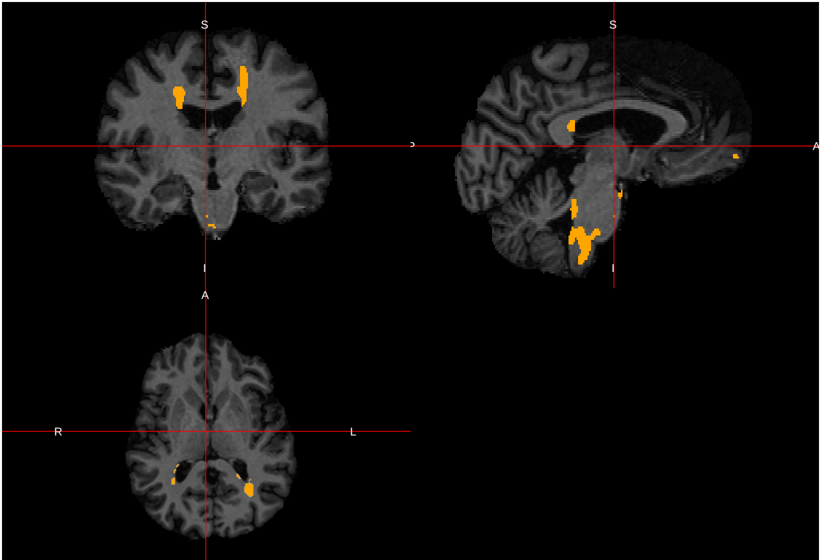
Default OASIS Model

- To evaluate how the default model performs, we need to compare the predictions to a gold standard.
- Let's therefore obtain OASIS probability maps for our training subjects.
- We will use the default threshold to binarize.

```
default_predict_tr = function(x){
  res = oasis_predict(
      flair=tr_flairs[[x]], t1=tr_t1s[[x]],
      t2=tr_t2s[[x]], pd=tr_pds[[x]],
      brain_mask=tr_masks[[x]],
      preproc=FALSE, normalize=TRUE,
      model=oasis::oasis_model, binary=TRUE)
  return(res)
}
default_probs_tr = lapply(1:5, default_predict_tr)
```

Default OASIS Model Results

- Here's the T1 volume for training subject 05 with the OASIS segmentation overlayed.



Default OASIS Model Results

- The average dice coeffients (over the two gold standards) for the training subjects are: 0.49, 0.69, 0.43, 0.29, 0.26.

Improving Results

- The default model is picking up a lot of false positives in the lower brain and spinal chord (check this)
- We might improve the results by re-training the OASIS model using our five training subjects.
- To retrain the model using new data, binary masks of gold standard lesion segmentations are needed and should be in T1 space.

Making OASIS data frames

- OASIS requires a particular data frame format
- Includes an option to preprocess your data (preproc)
- Includes an option to normalize the intensities of your data using whole-brain normalization (normalize)
- make_df() below is a helper function

```
make_df = function(x){
  res = oasis_train_dataframe(
      flair=tr_flairs[[x]], t1=tr_t1s[[x]], t2=tr_t2s[[x]],
      pd=tr_pds[[x]], gold_standard=tr_golds[[x]],
      brain_mask=tr_masks[[x]],
      preproc=FALSE, normalize=TRUE, return_preproc=FALSE)
  return(res$oasis_dataframe)
}
oasis_dfs = lapply(1:5, make_df)
```

Training OASIS

- The function `oasis_training` takes the data frames we made and fits a logistic regression, where the outcome vector consists of all subjects' voxel-level data (top 85% in intensity)
- The function `do.call` is a useful R function that applies the function named in the first argument to all elements of the list specified in the second argument.

```
model = do.call("oasis_training", oasis_dfs)
```

OASIS model object

- `model` is an object of type `glm`
- We see the covariates used and assosicated coefficients when we print the model:

```r
print(ms.lesion::ms_model)
```

```
Call:  glm(formula = formula, family = binomial, data = tra

Coefficients:
    (Intercept)         FLAIR_10            FLAIR        FLAI
        -5.6939           4.1041           1.4076        -2.1
          PD_10               PD            PD_20          T2
         4.7047           0.1739         -17.3328         9.9
             T2            T2_20            T1_10
         0.8376         -19.2016          12.5254         1.2
          T1_20   FLAIR_10:FLAIR   FLAIR:FLAIR_20        PD_10
       -27.9823          -1.0304          -3.4276         0.2
```

Trained OASIS Model Results

- The average dice coeffients (over the two gold standards) for the training subjects are: 0.64, 0.71, 0.62, 0.36, 0.36.

References

Sweeney, Elizabeth M, Russell T Shinohara, Navid Shiee, Farrah J Mateen, Avni A Chudgar, Jennifer L Cuzzocreo, Peter A Calabresi, Dzung L Pham, Daniel S Reich, and Ciprian M Crainiceanu. 2013. "OASIS Is Automated Statistical Inference for Segmentation, with Applications to Multiple Sclerosis Lesion Segmentation in MRI." *NeuroImage: Clinical* 2. Elsevier: 402–13.