MS Lesion Segmentation

Background

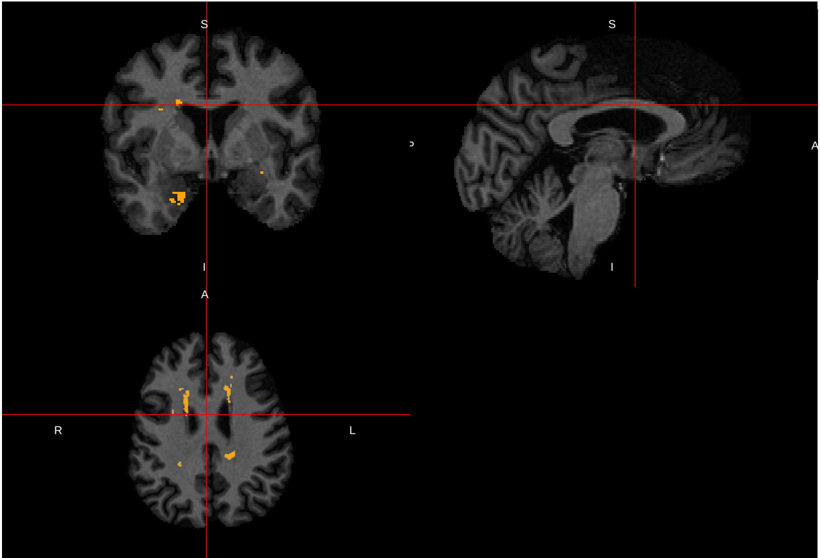
- Obtaining manual lesion segmentations is often resource intensive.
- Accurate and efficient methods for automatic segmentation are necessary for scalability and research progress.

Goals of this tutorial

- 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 a '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.
- The OASIS model is based on a logistic regression of the gold standard manual segmentation labels on the images, smoothed versions of the images, and some interaction terms (i.e., supervised learning).

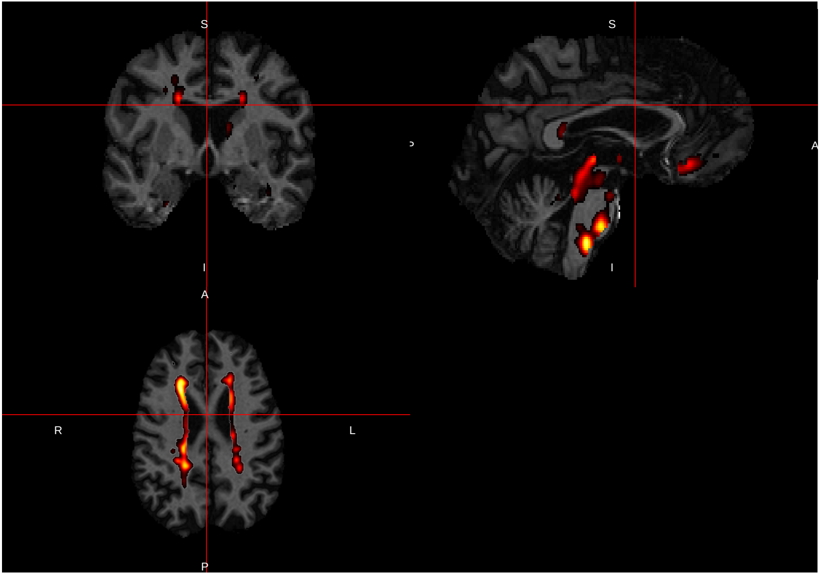
Default OASIS Model

- The OASIS library comes with default parameters that can be used to generate probability maps for new test subjects.
- The default model was trained on approximately 100 MS subjects and 30 healthy subjects with manual segmentations.
- Here we apply the function `oasis_predict` with the default model to obtain OASIS probability maps for the test subjects.

```r
library(oasis)
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:

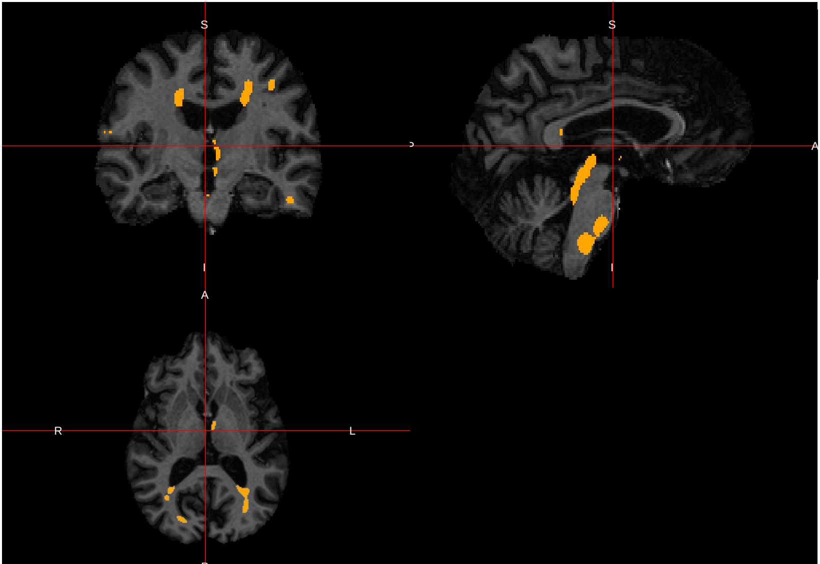


Thresholding

- 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 $= 0.16$).
- 0.16 was obtained via a validation set allowing for a 0.5% false positive rate.
- 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:



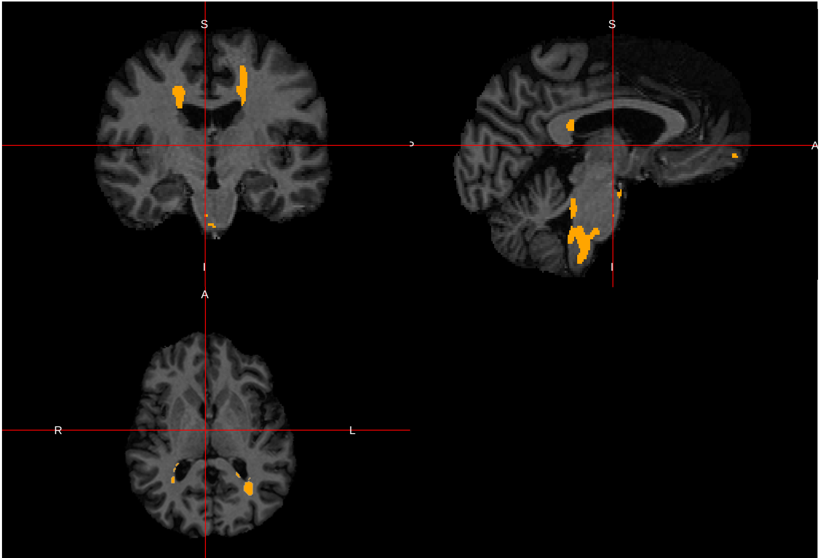
Default OASIS Model

- 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.

```r
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 dice coeffients for the training subjects compared to raters 1 (left) and 2 (right) are:

	Rater 1	Rater 2
01	0.4724006	0.4938917
02	0.6900361	0.6860189
03	0.362001	0.4316734
04	0.284585	0.2891665
05	0.3083417	0.2638682

Improving Results

- The default model is picking up a lot of false positives in the spinal cord.
- We might improve the results by re-training the OASIS model using our five training subjects.
- To re-train 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, which we create using the function `oasis_train_dataframe`.
- Includes an option to preprocess your data (`preproc`), which does (1) inhomogeneity correction using `fsl_biascorrect` and (2) rigid coregistration using `flirt` to the T1 space.
- Includes an option to whole-brain intensity normalize (`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_golds2[[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 using labels and features from a subset of voxels in each subject's brain mask (top 85% in FLAIR 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.
- Below, `model` is a `glm` object that stores the estimated parameters from the logistic regression.

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

OASIS model object

```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.
          PD_10               PD            PD_20            T
         4.7047           0.1739         -17.3328          9.
             T2            T2_20            T1_10
         0.8376         -19.2016          12.5254          1.
          T1_20   FLAIR_10:FLAIR   FLAIR:FLAIR_20         PD_1
       -27.9823          -1.0304          -3.4276          0.
       PD:PD_20         T2_10:T2         T2:T2_20         T1_1
        -1.1567          -0.9565           1.5197         -1.
       T1:T1_20
         4.6929
```

Trained OASIS Model Results

- Using the same threshold of 0.16.
- Dice coeffients for the training subjects:

	Rater 1	Rater 2
01	0.6281593	0.6438359
02	0.7088758	0.711435
03	0.5341028	0.6180772
04	0.3621744	0.3594041
05	0.4105148	0.3563922

Improvement

- Percent improvement in dice over the default model:

	Rater 1	Rater 2
01	32.9717435	30.359724
02	2.7302493	3.7048641
03	47.5418144	43.1816695
04	27.2640758	24.2896848
05	33.1363268	35.0645052

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.