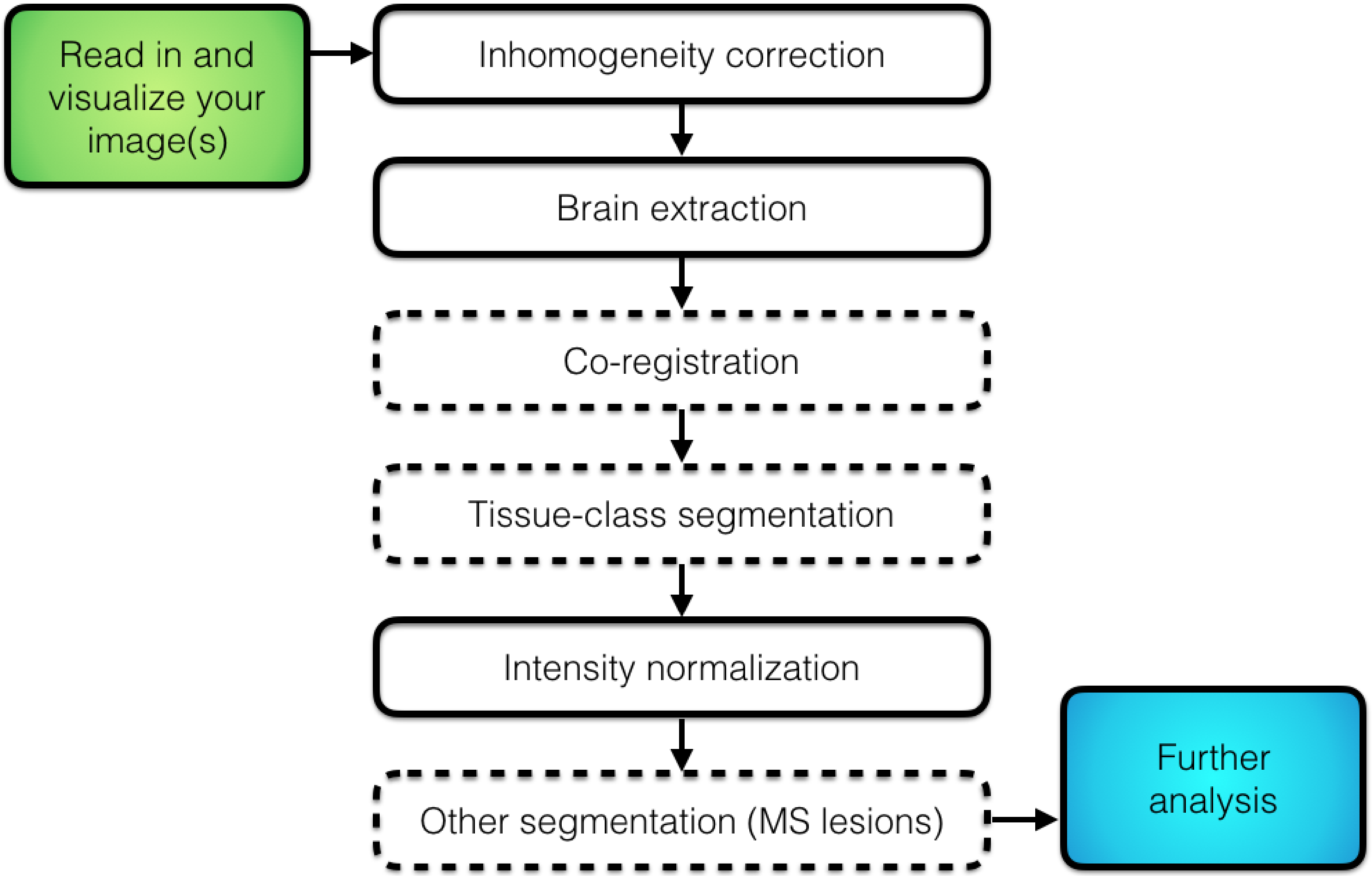
MS Lesion Segmentation

Overall Pipeline



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Background

- Obtaining manual lesion segmentations is often resource intensive.
  - "Gold standard": Inter- and Intra-rater variability.
- Accurate and efficient methods for automatic segmentation are necessary for scalability and research progress.
- In this tutorial, we will learn how to train and apply OASIS (Sweeney et al. 2013), an automatic lesion segmentation model, to obtain predicted lesion probability maps.
  - Relies on intensity-normalized data.

MS Lesion Segmentation with OASIS

- **O**ASIS is **A**utomated **S**tatistical **I**nference for **S**egmentation (Sweeney et al. 2013).
- OASIS takes FLAIR, T1, T2, and PD (optional) images.
    - Produces OASIS probability maps of MS lesion presence.
    - These can be thresholded into a binary lesion segmentation.
- The OASIS model is based on a logistic regression.
    - Regress binary manual segmentation labels on the images, smoothed versions of the images, and some interaction terms (e.g., supervised learning).
- Performs well compared to common machine learning models (Sweeney et al. 2014)

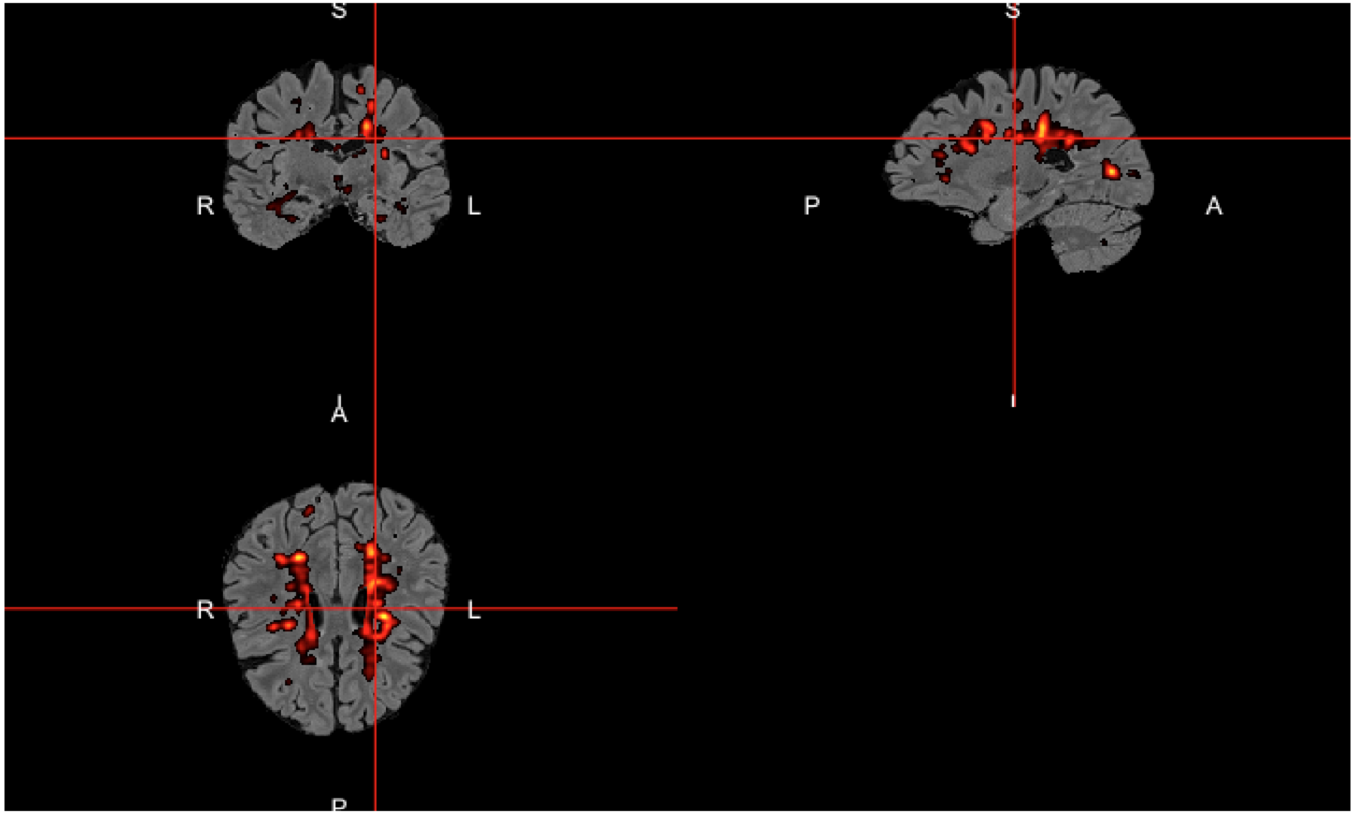
Default OASIS Model

- 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 `oasis_predict` with the default model to obtain OASIS probability maps for the test subjects.

```
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 of probability map

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



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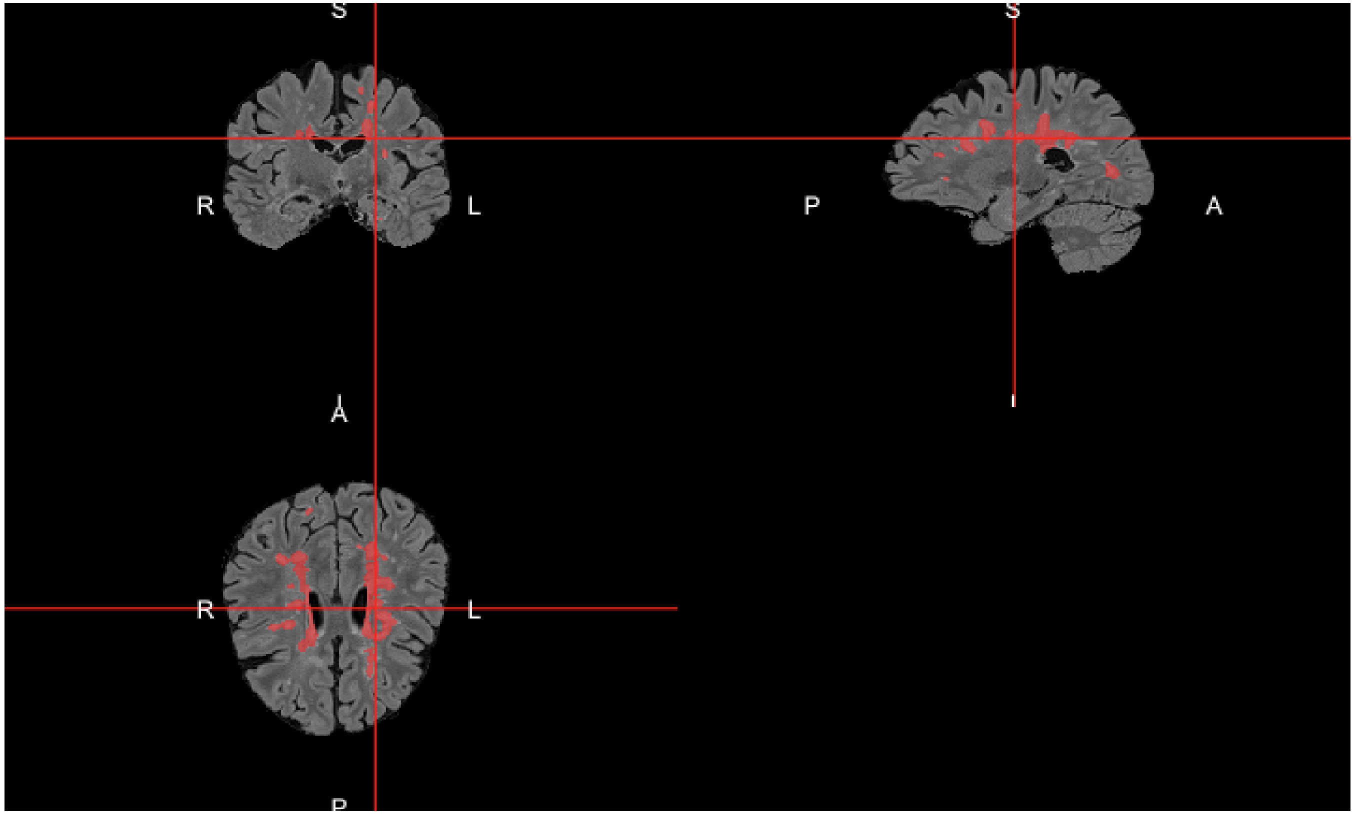
Thresholding: Getting a binary map

- 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 of binary map

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



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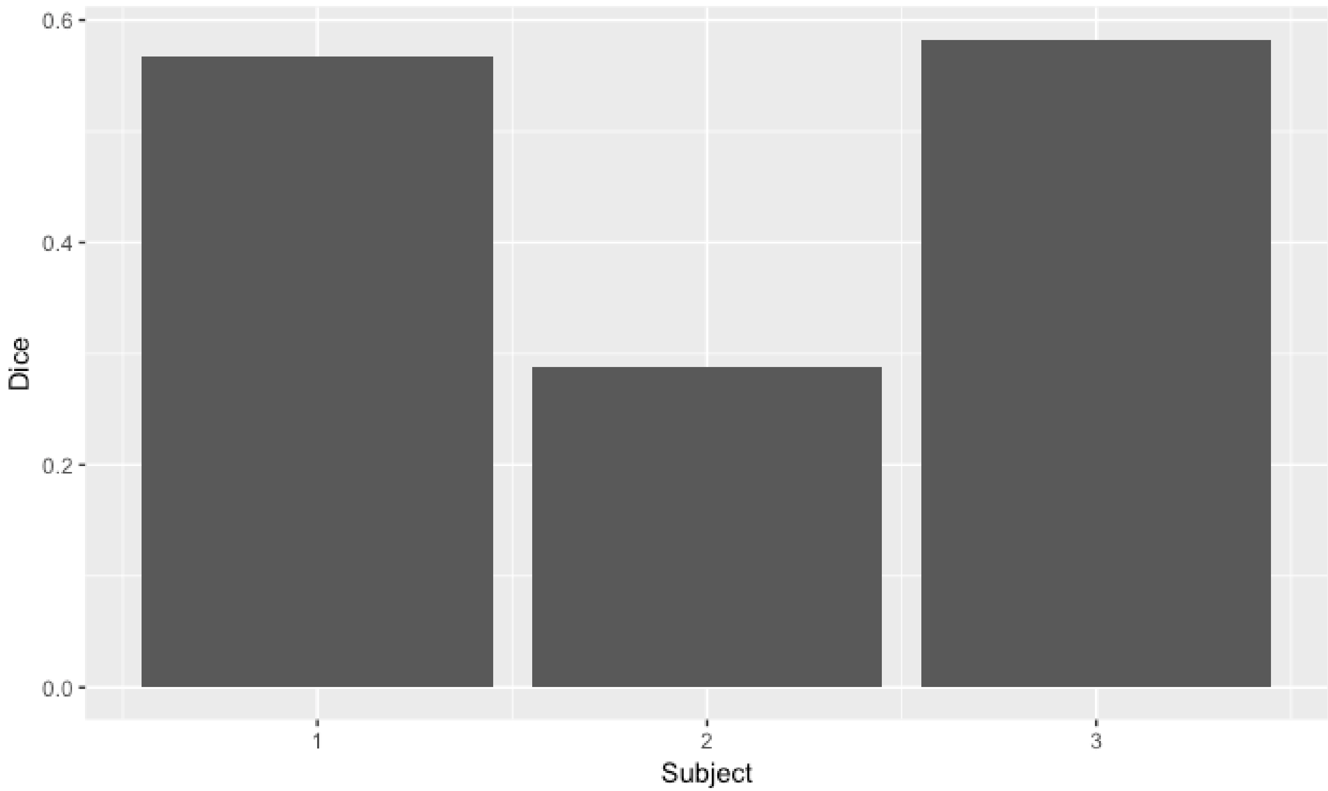
Default OASIS Model

- To evaluate how the default model with default threshold performs, we'll compare the predictions to our manual segmentations.
- Sorensen–Dice coefficient:
  - Similarity measure between two samples.
  - Ranges from 0 to 1.
  - (TP) - true positive, (FP) - false positive, (FN) - false negative.

$$D = 2TP2TP + FP + FN$$

Default OASIS Model Results

Dice coeffients for the test subjects



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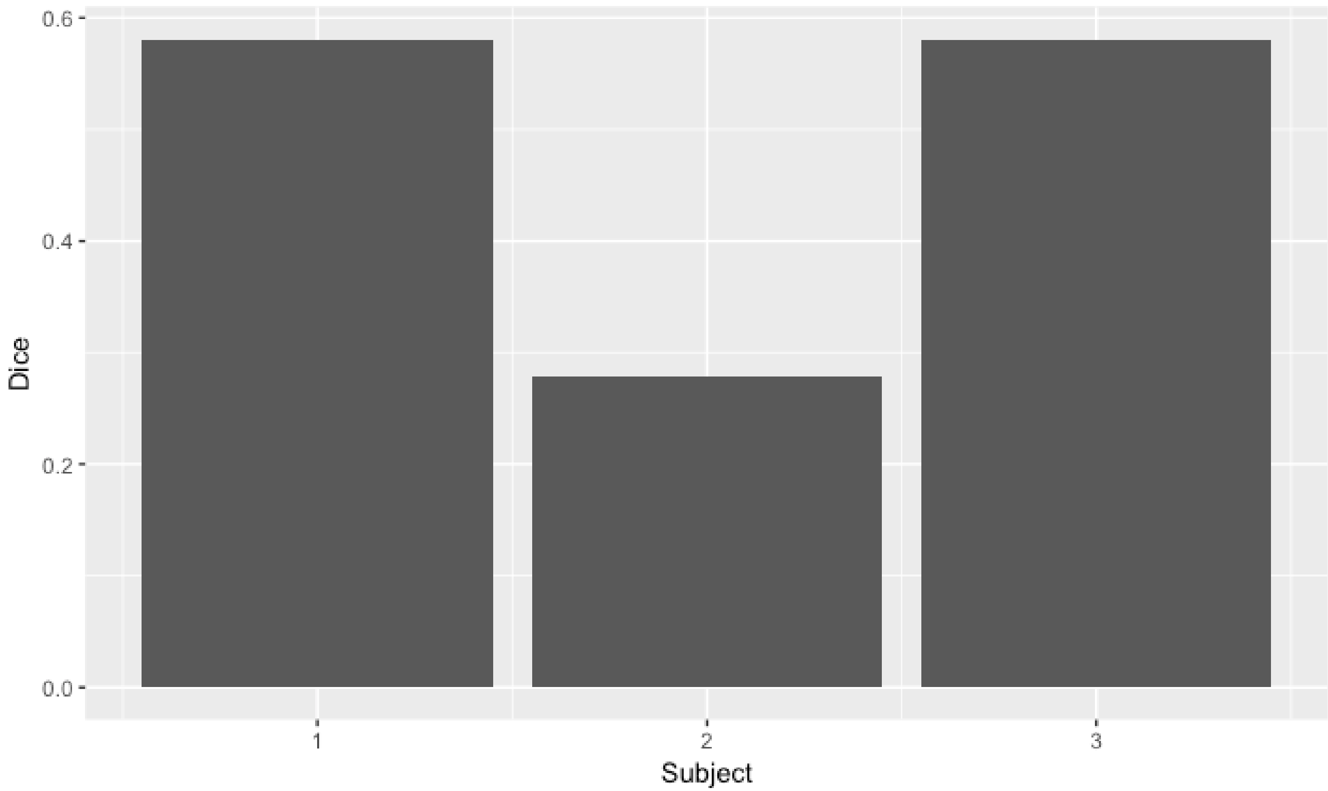
Improving Results

- We might be able to improve the results by adjusting the threshold.
- Let's optimize the threshold on the training data using a grid search (in practice, we might do cross-validation).

```
Threshold    0.050 0.100 0.150 0.200 0.250 0.300
Average Dice 0.242 0.272 0.273 0.261 0.231 0.194
```

Improving Results

- Turns out a coarse grid search chose a threshold of 0.15, so the results are nearly identical.



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Improving Results

- We might be able to further 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_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 using labels and features from a subset of voxels in each subject's brain mask (top 15% 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.

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

OASIS model object

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

```
Call:  glm(formula = form, family = binomial, data = df)

Coefficients:
   (Intercept)         FLAIR_10             FLAIR         FLAIR_20
      -4.79369         13.10386           1.14120        -18.77010
         T2_10               T2             T2_20            T1_10
       4.85370          1.09444          -7.06750         13.63554
            T1            T1_20    FLAIR_10:FLAIR   FLAIR:FLAIR_20
       1.04771        -21.09848          -1.28891          1.03121
      T2_10:T2         T2:T2_20          T1_10:T1         T1:T1_20
       0.09151          3.18903          -1.04701          3.14265

Degrees of Freedom: 3930444 Total (i.e. Null);  3930429 Residual
Null Deviance:       2691000
Residual Deviance: 1842000  AIC: 1842000
```


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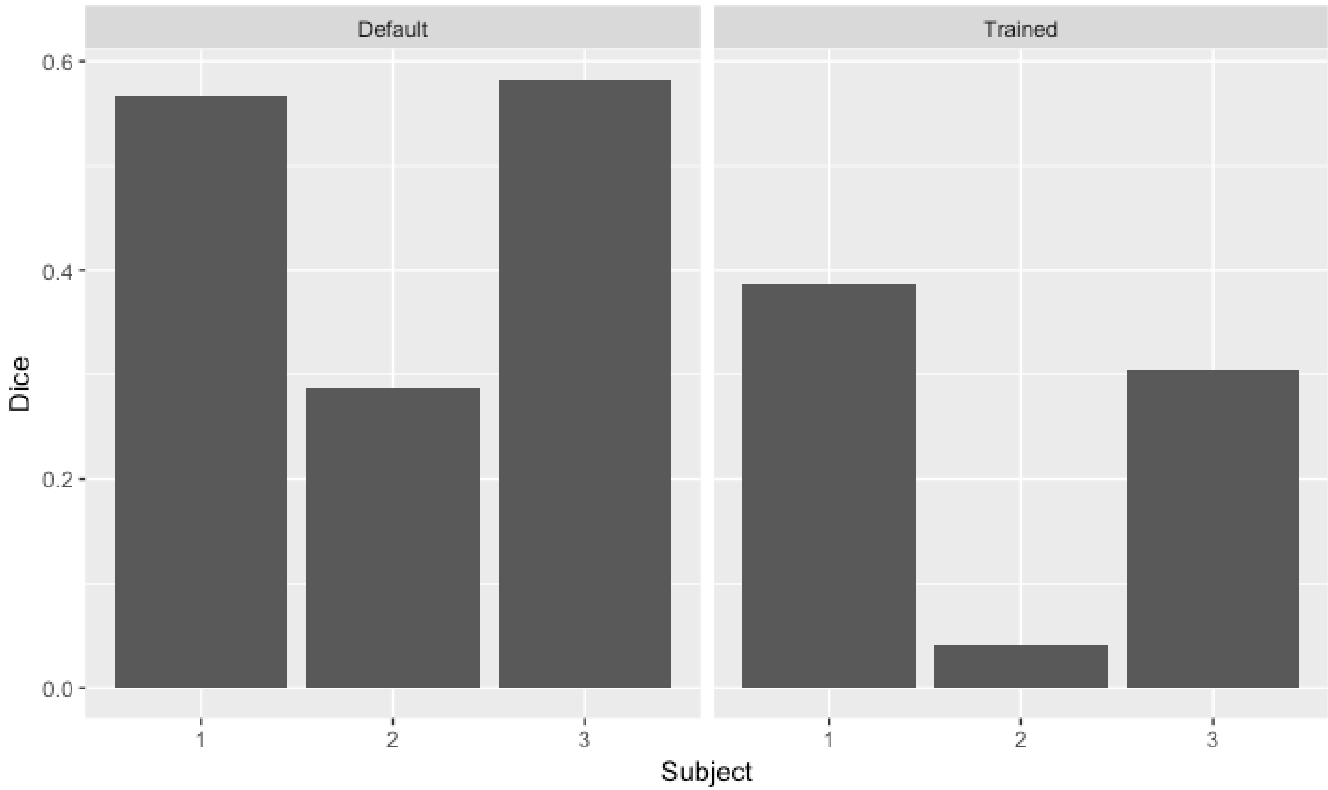
Trained OASIS Model Results

```
Threshold    0.050 0.100 0.150 0.200 0.25 0.300
Average Dice 0.253 0.324 0.346 0.346 0.33 0.294
```

- Using a threshold of 0.15.
- Dice coeffients for default vs. re-trained OASIS model.



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Improvement

- Percent improvement in Dice over the default model:

ID	Dice
01	-31.7
02	-85.7
03	-47.7

Website

http://johnmuschelli.com/imaging_in_r

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." 2. Elsevier: 402–13.

Sweeney, Elizabeth M, Joshua T Vogelstein, Jennifer L Cuzzocreo, Peter A Calabresi, Daniel S Reich, Ciprian M Crainiceanu, and Russell T Shinohara. 2014. "A Comparison of Supervised Machine Learning Algorithms and Feature Vectors for MS Lesion Segmentation Using Multimodal Structural MRI." 9 (4). Public Library of Science: e95753.