Module 29:
Performing MVPA II

Performing MVPA

- The process of performing MVPA follows a series of steps:
  - Defining features and classes
  - Feature selection
  - Choosing a classifier
  - Training and testing the classifer
  - Examining results

Training and Testing

- To accurately assess the performance of a classifier when applied to a new data set, it is critical to use separate data to train and test the classifier.
- Ideally, we would like to train a classifier using as much of the available data as possible.
  - However, this leaves little to test with.
- One approach to balance this problem is to use cross validation.

K-fold Cross-validation

- Procedure:
  - Divide dataset into K parts, or folds.
  - Leave one fold out
  - Train on the remaining K-1 folds
  - Predict observations on omitted fold
  - Repeat for each fold in turn
  - Compute accuracy of all predictions made

Choosing K

- If unbiased accuracy assessment is important, than use more folds.
  - Less error using large training data.

- If parameter optimization is important, than use fewer folds.
  - More stable estimate of error using large test data.

- In practice, 5 or 10 fold is often used as a compromise.

Comments

- When performing cross-validation it is important that each fold contains observations from each class.

- The classes should be roughly balanced in the cross-validation procedure.
  - Stratification can be used to guarantee that each class is adequately represented.

- One should be careful to include correlated observations in the same fold.

Comments

- Cross-validation provides a method for choosing between different types of classifiers and determining certain parameter estimates.

- Final classifier weights can be obtained in a number of ways, such as averaging the weights across folds.

Assessing Accuracy

- We often want to determine the accuracy of a classifier to determine whether it works better than chance.
- A simple approach is to use a binomial test with p(success)=0.5 per trial.
- A more accurate way to quantify performance is to use resampling methods.

Comments

- It is important to examine the accuracy for all classes of observations, rather than computing the overall accuracy across observations.
- If almost all of the observations fall in the same class than assigning all new observations to that class will give a high overall accuracy.

Comments

- For example, if 90% of all observations fall in class A then a classifier that always assigns new observations to class A will have 90% overall accuracy.

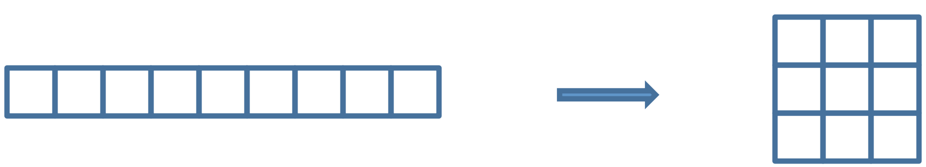
- It will also have a 100% accuracy of correctly classifying class A observation.

- However, it will have a 0% accuracy of correctly classifying class B observations.

Weight Maps

- An important question is determining which voxels drive the classification.

- The classifier weights can be mapped onto the brain to provide information about each voxels contribution to the classifier performance.
  - Different classifiers may provide different maps as they are sensitive to different features.



$\underline{w} = (w_1, \ldots w_V)$

Interpretability

- In fMRI it is important to make analysis choices that balance interpretability with predictive power.

- Certain methods may give good predictions but the resulting voxel weights may be difficult to interpret and may not generalize to new subjects.

End of Module