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PyMVPA: A Python toolbox for classifier-based data analysis

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Classifier-based analysis: Where is the software?

Advantages of classifier-based analysis:

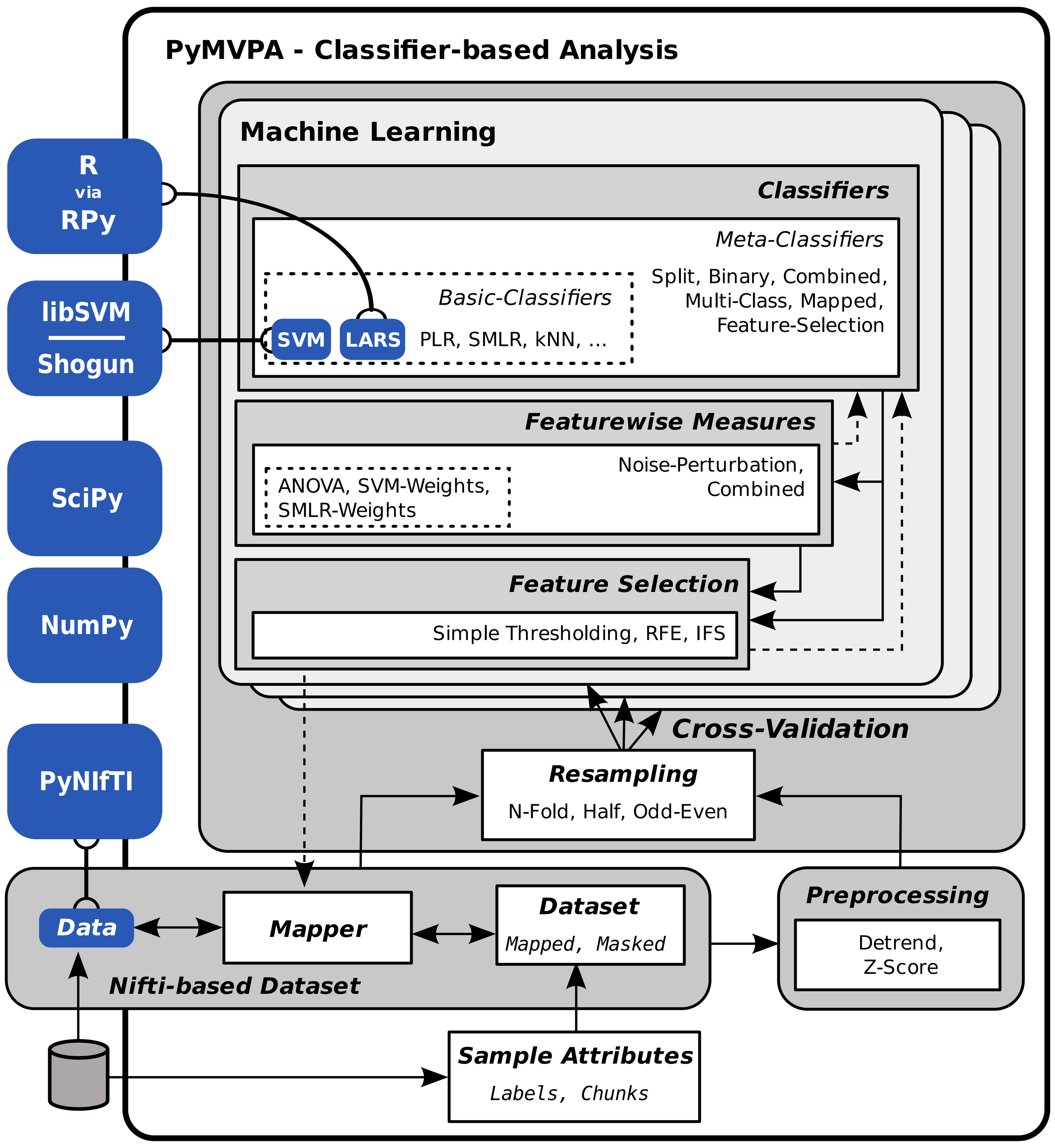
- Multivariate method
- Can focus on distributed patterns instead activation foci
- Direct quantifyable link between neuroimaging data and experimental manipulation (O'Toole et al, 2007)
- Suitable for high-resolution fMRI imaging (Kriegeskorte et. al, 2007)

Increasing number of publications applying classifier-based analysis to neuroimaging data (e.g. Haxby et al., 2001; Kamitani & Tong, 2005; Hanson et al., 2004; Haynes & Rees, 2007; Hanson & Halchenko, 2008), but only few software packages to facilitate this type of analysis, which are available to a broad audience (*3dsvm*, LaConte et al., 2005; *MVPA toolbox*, Detre et al., 2006).
But: wealth of machine learning software (www.mloss.org)

There is a need for a unifying framework to bridge between establish neuroimaging and machine learning software.

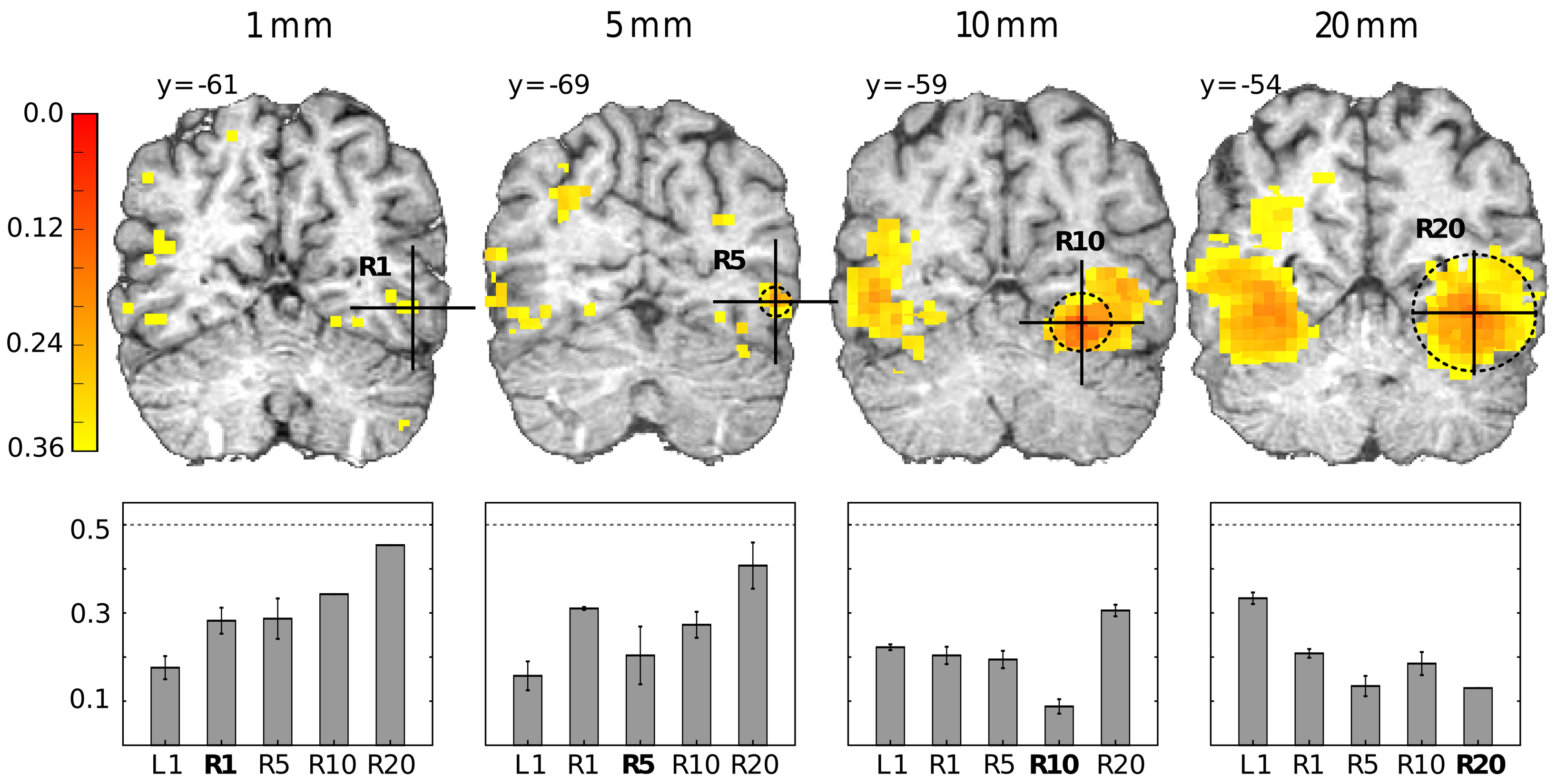
PyMVPA Features

- User-centered programmability with a intuitive user interface: Object-oriented toolbox design leading to readable and verifyable code.
- Extensibility: Modular interface to connect extensions in multiple programming languages.
- Transparent reading and writing of datasets: NIfTI support for input and output and additional generic support of various binary and plain text format.
- Portability: Should run on anything supported by Python.
- Open source software: MIT-licensed free software.



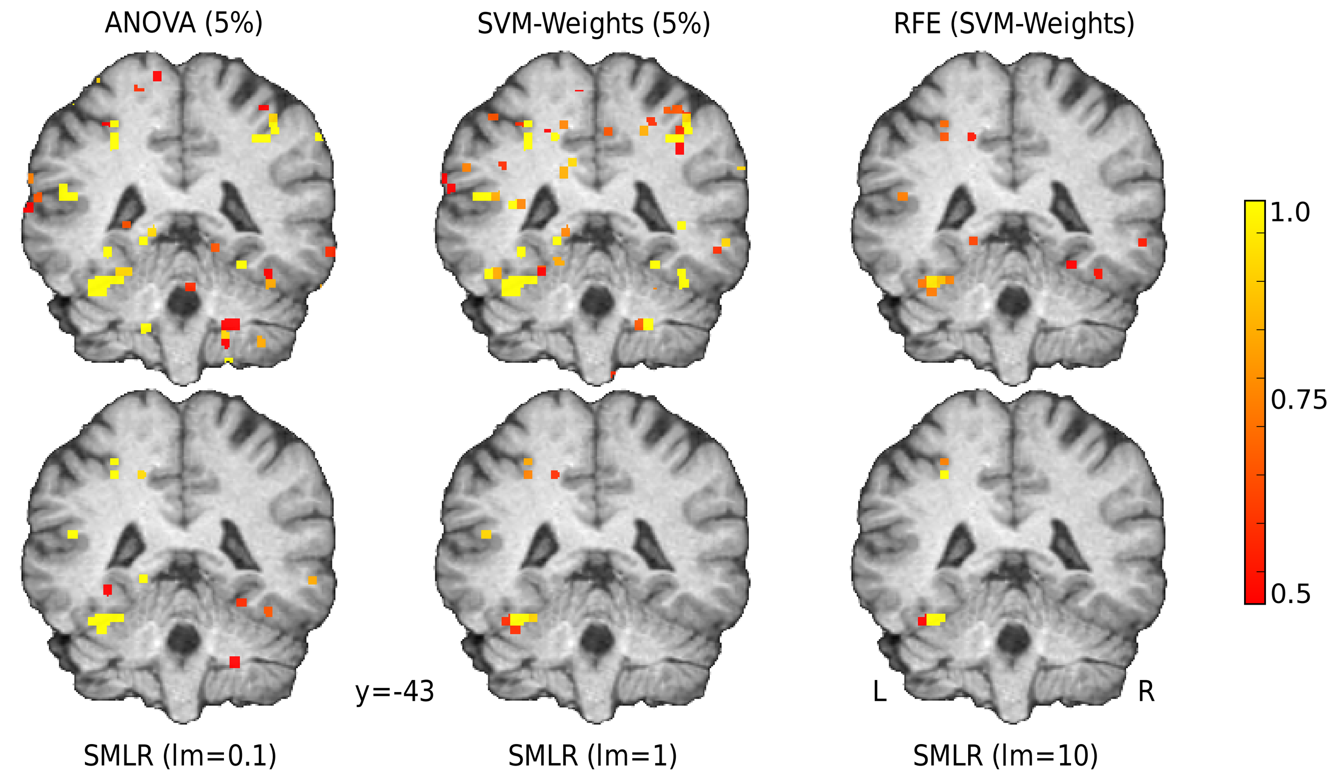
Example: Multiple ROI analysis with a Searchlight

```
attr = SampleAttributes('sample_attr_filename.txt')
dataset = NiftiDataset(
              samples='subj1_bold.nii.gz',
              labels=attr.labels, chunks=attr.chunks,
              mask='subj1_roi_mask.nii.gz')
cv = CrossValidatedTransferError(
        TransferError(LinearCSVMC()), OddEvenSplitter())
sl = Searchlight(cv, radius=5)
sl_map = sl(dataset)
dataset.map2Nifti(array(sl_map)).save('slight_5mm.nii.gz')
```



Example: Flexible feature selection

```
attr = SampleAttributes('sample_attr_filename.txt')
dataset = NiftiDataset(samples='subj1_bold.nii.gz',
                       labels=attr.labels, chunks=attr.chunks)
clf = LinearCSVMC()
clf = FeatureSelectionClassifier( clf,
      SensitivityBasedFeatureSelection( OneWayAnova(),
         FractionTailSelector(0.05,  mode='select')))
cv = CrossValidatedTransferError( TransferError(clf),
        NFoldSplitter(), enable_states=['confusion'])
error = cv(dataset)
```



CATS vs. SCISSORS classification. Data from one participant from Haxby et al., 2001.

The PyMVPA toolbox is available at

http://pkg-exppsy.alioth.debian.org/pymvpa/

PyMVPA mailing list

pkg-exppsy-pymvpa@lists.alioth.debian.org

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