Introduction

Main aims of pattern recognition techniques for neuroimaging:
- development of accurate diagnosis systems;
- identification of brain regions related to the disease.

Kernel methods (e.g. SVM, MKL) [1,2] commonly used:
- Good accuracy with linear kernels;
- Good interpretability through feature weight maps [3].

Tree approaches not really popular in neuroimaging but:
- State-of-the-art accuracy on many problems with minimal tuning;
- Results interpretable through variable importance scores.

Aim: to study tree methods and show their good behavior against those of traditional methods such as SVM and MKL.

Methods

Data:
Methods are tested on two datasets:
- IXI [4]:
  - Structural MRI;
  - 170 aged vs. 99 young individuals;
  - We work in particular with scalar momentums obtained with SPM8, like in [5].
- OASIS [6]:
  - Structural MRI;
  - 50 demented vs. 50 non-demented old subjects;
  - Age and gender matched;
  - Preprocessing with SPM8.

Machine learning methods:
- Linear support vector machines (SVM);
- Multiple kernel learning (MKL);
- Single regression tree (ST);
- Random forests [7] (RF);
- Extremely randomized trees [8] (ET);
- Logitboost [9] with ST (LB) and with ET (LB).

Assessment:
- Cross-validation (CV);
- 5 folds for IXI & 10 folds for OASIS;
- Nested CV for parameter optimization of SVM, MKL & LB.

Weight map and weight map per region (MrP) built from:
- Weight vector for SVM;
- Feature importance scores for ST, RF & ET;
- Number of times a voxel is chosen to split a node for LB;
- Aggregation of weights with AAL atlas for MrP.

Decision tree & Ensemble methods

Tree Ensemble Methods:
- Combine the prediction of several trees;
- Trees grown either independently (as RF or ET) or sequentially (Boosting);
- Improve the bias-variance trade-off of single trees.

Results

Competitive accuracy:

<table>
<thead>
<tr>
<th>Method</th>
<th>IXI error rate (%)</th>
<th>OASIS error rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM</td>
<td>1.49</td>
<td>35.00</td>
</tr>
<tr>
<td>MKL</td>
<td>3.72</td>
<td>45.00</td>
</tr>
<tr>
<td>Single tree</td>
<td>15.24</td>
<td>44.00</td>
</tr>
<tr>
<td>Random forests</td>
<td>1.71 ± 0.20</td>
<td>35.50 ± 0.97</td>
</tr>
<tr>
<td>Extremely randomized trees</td>
<td>1.86 ± 0.30</td>
<td>33.50 ± 1.51</td>
</tr>
<tr>
<td>Logitboost LB</td>
<td>2.23</td>
<td>37.00</td>
</tr>
<tr>
<td>Logitboost LB</td>
<td>0.76 ± 0.12</td>
<td>33.60 ± 0.52</td>
</tr>
</tbody>
</table>

Table 1: Summary of method performance for both datasets.

Good interpretability:
- Similar important regions;
- Sparser models with tree-based methods.

Conclusion

We show that tree based methods can achieve competitive accuracy and provide interpretable models for the analysis of neuroimaging data and thus we believe that tree methods are a promising alternative to traditional methods in this area.

References


Acknowledgements & sponsors: Belgian National Fund for Scientific Research (F.R.S-FNRS) – University of Liège (UG) – Cyclotron Research Centre (CRC)