TECHNISCHE UNIVERSITÄT
KAISERSLAUTERN

11.2 Random Forests

Machine Learning 1: Foundations

Marius Kloft *(TUK)*

Bagging

One major problem with trees is their high variance:

- often a small change in the data can result in a very different series of splits

Bagging averages many trees to reduce this variance

Bagging ("Bagging Predictors" 1996)

Definition

1: randomly draw data sets **with replacement** from the training data, each having the same size as the original training set
2: grow a tree on each data set
3: average the resulting prediction functions (regression) or perform majority vote (classification)

Note:

- in principle, this trick can be applied to any arbitrary learning machine algorithm (e.g., SVM, KRR, neural network)
- but in practice it works best with (small) decision trees
- the resulting ensemble of trees is called a **forest**

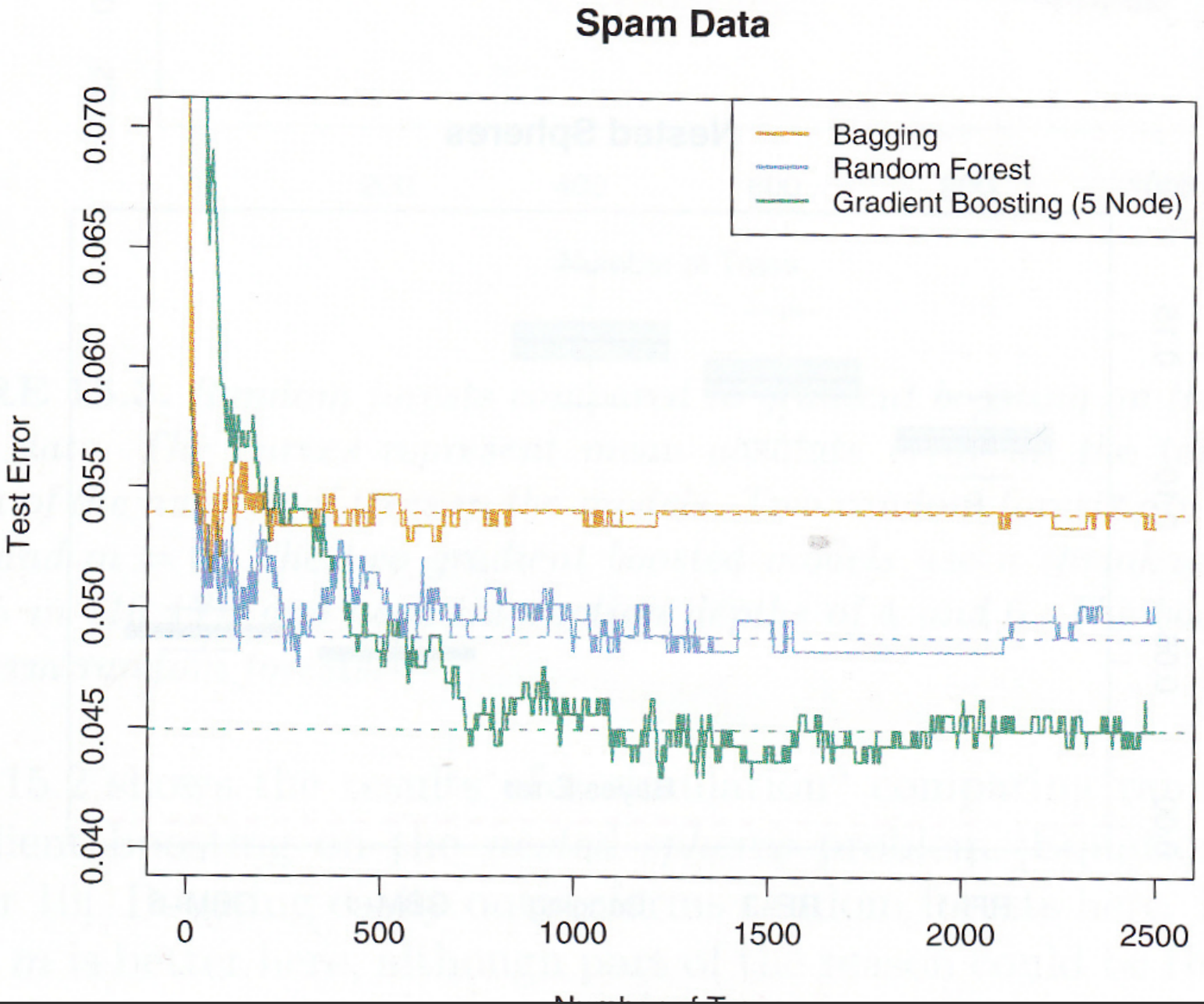
Random Forests (Breiman, 2001)

Definition

Pretty much the same as bagging (of decision trees) except for one difference:

- when growing a tree of the forest, for each split of an internal node in the tree, we randomly select a subset of $m < d$ many features.
- The optimal split feature j is determined only among those m features.

Example (SPAM data)



Conclusion

Journal of Machine Learning Research 15 (2014) 3133-3181 Submitted 11/13; Revised 4/14; Published 10/14

Do we Need Hundreds of Classifiers to Solve Real World Classification Problems?

Manuel Fernández-Delgado MANUEL.FERNANDEZ.DELGADO@USC.ES
Eva Cernadas EVA.CERNADAS@USC.ES
Senén Barro SENEN.BARRO@USC.ES
CITIUS: Centro de Investigación en Tecnoloxías da Información da USC
University of Santiago de Compostela
Campus Vida, 15872, Santiago de Compostela, Spain

Dinani Amorim DINANIAMORIM@GMAIL.COM
Departamento de Tecnologia e Ciências Sociais- DTCS
Universidade do Estado da Bahia
Av. Edgard Chastinet S/N - São Geraldo - Juazeiro-BA, CEP: 48.305-680, Brasil

Editor: Russ Greiner

Abstract

We evaluate **179 classifiers** arising from **17 families** (discriminant analysis, Bayesian, neural networks, support vector machines, decision trees, rule-based classifiers, boosting, bagging, stacking, random forests and other ensembles, generalized linear models, nearest-neighbors, partial least squares and principal component regression, logistic and multinomial regression, multiple adaptive regression splines and other methods), implemented in Weka, R (with and without the caret package), C and Matlab, including all the relevant classifiers available today. We use **121 data sets**, which represent **the whole UCI** data base (excluding the large-scale problems) and other own real problems, in order to achieve significant conclusions about the classifier behavior, not dependent on the data set collection. **The classifiers most likely to be the bests are the random forest** (RF) versions, the best of which (implemented in R and accessed via caret) achieves 94.1% of the maximum accuracy overcoming 90% in the 84.3% of the data sets. However, the difference is not statistically significant with the second best, the SVM with Gaussian kernel implemented in C using LibSVM, which achieves 92.3% of the maximum accuracy. A few models are clearly better than the remaining ones: random forest, SVM with Gaussian and polynomial kernels, extreme learning machine with Gaussian kernel, C5.0 and avNNet (a committee of multi-layer perceptrons implemented in R with the caret package). The

Acknowledgment

This lecture is based on Hastie *et al.*, 2009, Chapter 9 and 15.
The figure on Slide 5 is taken from Hastie *et al.*, 2009.

Refs I


Bagging predictors, *Machine Learning*, vol. 24, no. 2, pp. 123–140, 1996.


L. Breiman, Random forests, *Machine learning*, vol. 45, no. 1, pp. 5–32, 2001.


T. Hastie, R. Tibshirani, and J. Friedman, The elements of statistical learning, 2nd editiion. Springer series, 2009.