

# Bagging, Random Forests, Extra Trees

## Extra Trees

# Extra-Trees

Taking randomization one step further...

- ① Draw a random sample  $m$  from the  $p$  predictors (w/o Bootstrapping)
- ② Draw a **random split** per feature
  - Numerical attribute  $a$ 
    - Draw a cut-point  $a_c$  uniformly in  $[a_{min}, a_{max}]$
    - Return the split  $[a < a_c]$
  - Categorical attribute  $a$ 
    - Compute  $\mathcal{A}_s$ , the subset of values of  $a$  that appear in the training data
    - Draw a subset  $\mathcal{A}_1$  of  $\mathcal{A}_s$  and a subset  $\mathcal{A}_2$  of  $\mathcal{A} \setminus \mathcal{A}_s$
    - Return the split  $[a \in \mathcal{A}_1 \cup \mathcal{A}_2]$
- ③ Split node using the best of these random splits

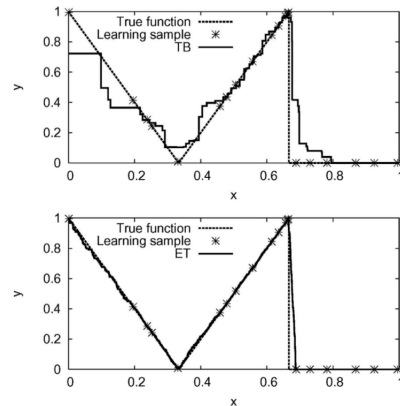
→ Extremely Randomized Trees (Geurts et al. 2006)

# Extra-Trees

Figure: Comparison of Tree Bagging (TB) and Extra Trees (ET) models (example, Geurts et al. 2006)

## Advantages of Extra-Trees

- Strong variance reduction
  - Random cut-points enforce de-correlation
  - *Totally randomized trees* with  $m_{try} = 1$
- Small(er) bias?
  - Usage of full training sample
- Computational benefits
  - Simple node splitting procedure



# Summary

- Resample-and-combine technique
- Bagging mimics averaging over several training sets
- Resampling utilized in various ML contexts
- Stabilizes predictions from high-variance methods (e.g., CART)
- Lower-level effect: Equalizes influence of outliers (Grandvalet 2004)

# Software Resources

## Resources for R

- Standard package to grow RFs: `randomForest`
- Fast implementation of RFs: `ranger`
- Extremely Randomized Trees: `extraTrees`
- Ensembles of Conditional Inference Trees: `cforest`
- Classification and Regression Training: `caret`
  - <https://topepo.github.io/caret/>

# References

- Berk, R. A. (2006). An Introduction to Ensemble Methods for Data Analysis. *Sociological Methods & Research*, 34(3), 263–295.
- Biau, G., Scornet, E. (2015). *A Random Forest Guided Tour*. arXiv: 1511.05741.
- Breiman, L. (2001). Random forests. *Machine Learning* 45(1), 5–32.
- Breiman, L. (1996). Bagging Predictors. *Machine Learning*, 24(2), 123–140.
- Geurts, P., Ernst, D., Wehenkel, L. (2006). Extremely Randomized Trees. *Machine Learning* 63(1), 3–42.
- Grandvalet, Y. (2004). Bagging Equalizes Influence. *Machine Learning*, 55(3), 251–270.
- Hall, P., Samworth, R. J. (2005). Properties of bagged nearest neighbour classifiers. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 67: 363–379.
- Hastie, T., Tibshirani, R., Friedman, J. (2009). *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*. New York, NY: Springer.
- James, G., Witten, D., Hastie, T., Tibshirani, R. (2013). *An Introduction to Statistical Learning*. New York, NY: Springer.
- Strobl, C., Malley, J., Tutz, G. (2009). An Introduction to Recursive Partitioning: Rationale, Application and Characteristics of Classification and Regression Trees, Bagging, and Random Forests. *Psychological Methods* 14(4). 323–348.