

# Stacking Algorithm for Ensemble Modelling

Frederik Schreck

Course: Numerical Introductory Course  
Lecturer: Prof. Dr. Brenda López Cabrera  
Humboldt-Universität zu Berlin



## Motivation - The wisdom of the crowd

- The aggregation of individual guesses in groups is often superior to individual guesses - even to experts
- BUT: Only fulfilled under certain criteria
  - ▶ Variation of guesses
  - ▶ Independence of guesses
  - ▶ Decentralization
  - ▶ Algorithm



# Outline

1. Motivation ✓
2. Ensemble Learning
3. Decision Tree
4. Stacking algorithms
  - 4.1 Bagging and Random Forest
  - 4.2 Boosting and Gradient Boosting
  - 4.3 Bayes??
  - 4.4 Stacked Generalization
5. Potentials and Problems of Ensemble Learning
6. The German Credit Dataset
7. Sources



## Ensemble Learning - Terminology

### Machine Learning

- Part of computer science that uses statistical techniques to train models on data
- Typically used for prediction purposes

### Stacking and Ensemble Learning

- Idea is to combine hypotheses of multiple learning algorithms (base learners)
- Goal is to obtain a better predictive performance than with each of the single algorithms alone
- Mainly used in supervised learning
- Very flexible method



## Ensemble Learning

Which models to combine?

- Effective ensembling builds on diverse and little correlated models
- Best to use strong base learners

Similar criteria as mentioned in the Motivation!



## Decision Tree

- Idea: use a set of splitting rules to recursively partition the dataset.
- Classification trees:
  - ▶ Minimize impurity within nodes
- Regression trees:
  - ▶ Minimize variance of the response variable within nodes



## Decision Tree for classification

- Choice of splitting rule: maximizing information gain (IG) by decreasing node impurity (I)

$$IG_n = I_n - p_{n_1} * I(n_1) - p_{n_2} * I(n_2), \quad (1)$$

for node  $n$  with branching nodes  $n_1$  and  $n_2$ , and  $p_{n_i}$  as the fraction of cases in branching node  $n_i$

- How to measure impurity? Choices of splitting criteria:

$$\text{Entropy: } I(n) = - \sum_j^J p(c_j|n) * \log_2(p(c_j|n)) \quad (2)$$

$$\text{Gini impurity: } I(n) = 1 - \sum_j^J p(c_j|n)^2 \quad (3)$$

$$\text{Misclassification impurity: } I(n) = 1 - \max_j p(c_j), \quad (4)$$

Stacking Algorithm for Ensemble Modelling



for classes  $c_i, i \in J = \{1, 2, \dots\}$

## Decision Tree for classification

- Choice of stopping rule: A fully grown tree has pure leaf nodes and may overfit the data
  - ▶ Pre-pruning
  - ▶ Post-pruning





## Bagging

blalala



## Random Forest

blalala



# Boosting

blalala



# Gradient Boosting

blalala



# Bayes??

blalala



# Stacked Generalization

blalala



# Potentials and Problems of Ensemble Learning

blalala



## Sources



Kuncheva, L. I. and Whitaker, C. J. (2003).

Measures of diversity in classifier ensembles and their relationship with the ensemble accuracy.

*Machine learning*, 51(2):181–207.



Surowiecki, J. (2005).

*The Wisdom of Crowds*.

Anchor.

