

# Applied Machine Learning

## Lecture 2: Ensembles and random forests

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The slides are further development of Richard Johansson's slides

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# Overview

Introduction to ensembles

Implementing ensemble classifiers

Decision trees - recap

Random forest

Review and Closing

# Ensembles

The screenshot shows a web browser window displaying the Göteborgs Symfoniker website. The browser's address bar shows the URL: <https://www.gso.se/en/programme/concerts/barockakademien-goteborg-symfoniker-lerum-molnlycke/2019-10-12-18.00/>. The website's header includes a logo for Göteborgs Symfoniker and a navigation menu with links: PROGRAMME, THE CONCERT HALL, GÖTEBURG SYMPHONY ORCHESTRA, GSOplay, FOR CHILDREN, and CONTACT. On the right side of the header, there are icons for a calendar, search, user profile, and a menu. The main content area features a large photograph of the Baroque Academy performing in a concert hall. Overlaid on the bottom left of the photograph is a red box with the text: SAT 12 OCT 18.00. Below this, a white box contains the text: THE BAROQUE ACADEMY PLAYS IN LERUM & MÖLNLYCKE. At the bottom of the photograph, a small line of text reads: The Baroque Academy of Göteborgs Symphony Orchestra, Stefano Veggiani artistic director. A red button with the text 'GET NEWSLETTER' is located in the bottom left corner of the photograph area.

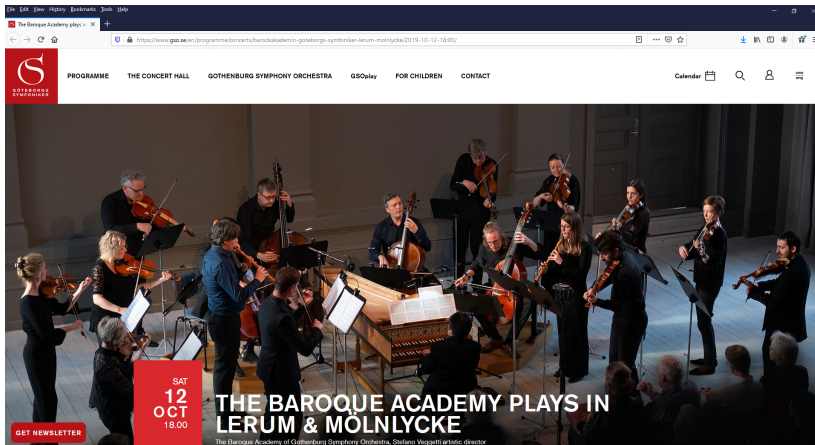
SAT  
12  
OCT  
18.00

THE BAROQUE ACADEMY PLAYS IN  
LERUM & MÖLNLYCKE

The Baroque Academy of Göteborgs Symphony Orchestra, Stefano Veggiani artistic director

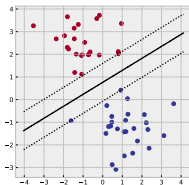
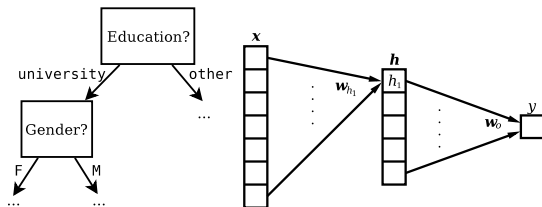
GET NEWSLETTER

# Ensembles



- ▶ In machine learning: combination of several models
  - ▶ of different types (e.g., decision tree & neural network)
  - ▶ of the same type but trained differently (e.g., random forests)

# Why use ensembles?



- ▶ To create a more powerful model by combining the strengths of individual/base models.
- ▶ To reduce overfitting
- ▶ **Diverse** classifiers can complement each other, average out individual mistakes

# Overview

Introduction to ensembles

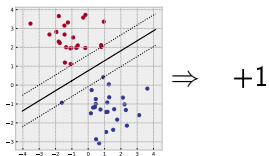
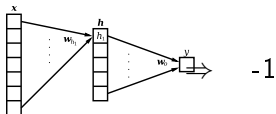
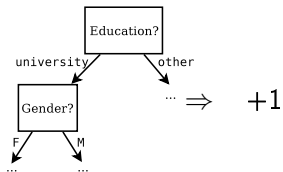
Implementing ensemble classifiers

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# Ensemble technique: Voting



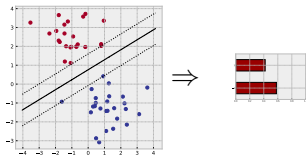
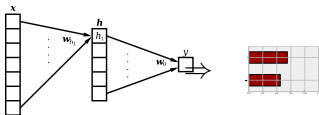
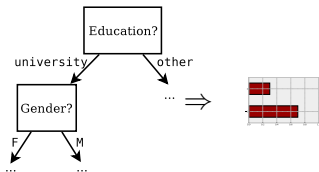
- ▶ Majority
- ▶ Weighted

## in scikit-learn

```
ensemble = [  
    ('lr', LogisticRegression()),  
    ('dt', DecisionTreeClassifier(max_depth=5)),  
    ('svc', LinearSVC()),  
    ('lr1', LogisticRegression(penalty='l1')),  
    ('mlp', MLPClassifier(hidden_layer_sizes=(8),  
                           max_iter=10000))  
]  
  
pipeline = make_pipeline(  
    DictVectorizer(),  
    StandardScaler(with_mean=False),  
    VotingClassifier(ensemble)  
)
```

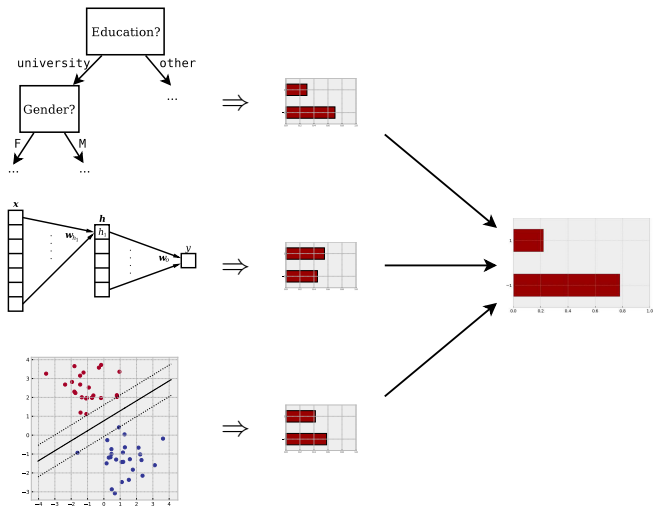


# Ensemble technique: Averaging

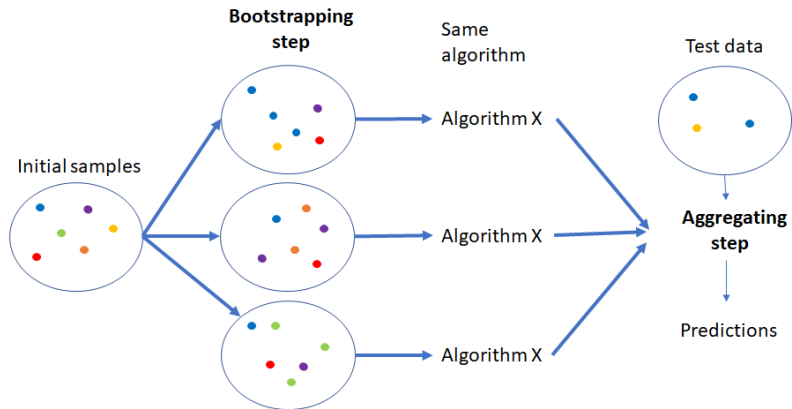


- ▶ Simple
- ▶ Weighted

# Ensemble technique: Stacking



# Ensemble technique: Bagging



# Implementation of bagging and its variant

- ▶ With random subsets of data
  - ▶ without replacement (called **pasting**)
  - ▶ with replacement (called **bagging**, short for **bootstrap aggregating**)
  - ▶ When to choose pasting vs bagging?
- ▶ With random subsets of features (called **feature bagging** or **random subspaces**)

# ensemble techniques in scikit-learn

- ▶ `sklearn.ensemble.VotingClassifier`
- ▶ `sklearn.ensemble.VotingRegressor`
- ▶ `sklearn.ensemble.StackingClassifier`
- ▶ `sklearn.ensemble.StackingRegressor`
- ▶ `sklearn.ensemble.BaggingClassifier`
- ▶ `sklearn.ensemble.BaggingRegressor`

# Overview

Introduction to ensembles

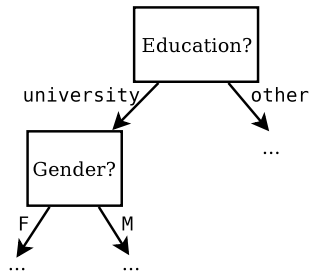
Implementing ensemble classifiers

Decision trees - recap

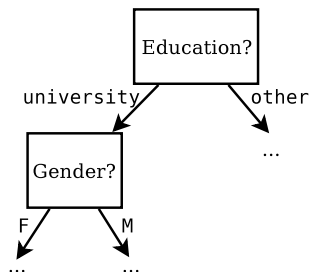
Random forest

Review and Closing

## Decision tree recap



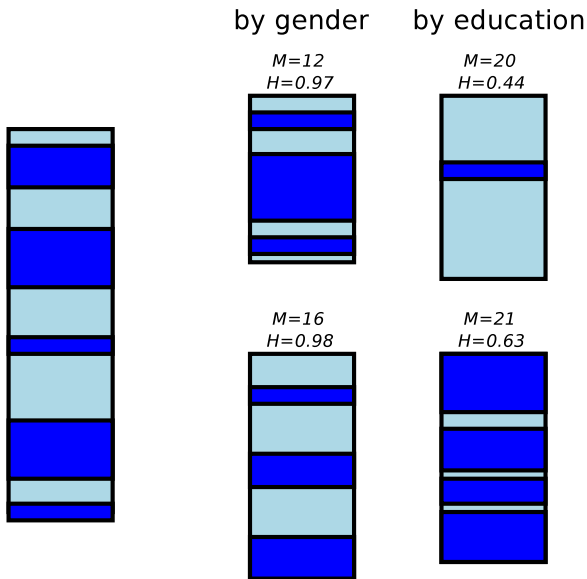
# Decision tree recap



- ▶ Algorithm (simplified):
  1. Select the feature  $F$  that gives the “best” split
  2. Make a tree with  $F$  at the top
  3. Split into subsets based on  $F$
  4. Make a tree for each subset



# Selecting the feature for the top node



# Decision trees aren't fantastic

*“Decision trees are a popular method for various machine learning tasks. Tree learning come[s] closest to meeting the requirements for serving as an off-the-shelf procedure for data mining, because it is invariant under scaling and various other transformations of feature values, is robust to inclusion of irrelevant features, and produces inspectable models. However, they are seldom accurate.”*

[Hastie et al., *The Elements of Statistical Learning*]

- ▶ Highly dependent on training data, tend to overfit
- ▶ All features are considered when splitting a node
- ▶ But there are several popular types of ensembles that typically build on decision trees

# Overview

Introduction to ensembles

Implementing ensemble classifiers

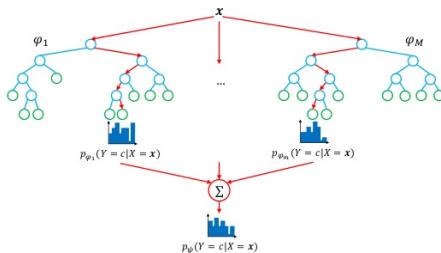
Decision trees - recap

**Random forest**

Review and Closing

# Random forest

- ▶ Is an ensemble of many decision trees built based on the same raw data and the same tree-algorithm
- ▶ Is a nonlinear estimator
- ▶ Are applicable for classification and regression
- ▶ Can take both numerical and categorical data

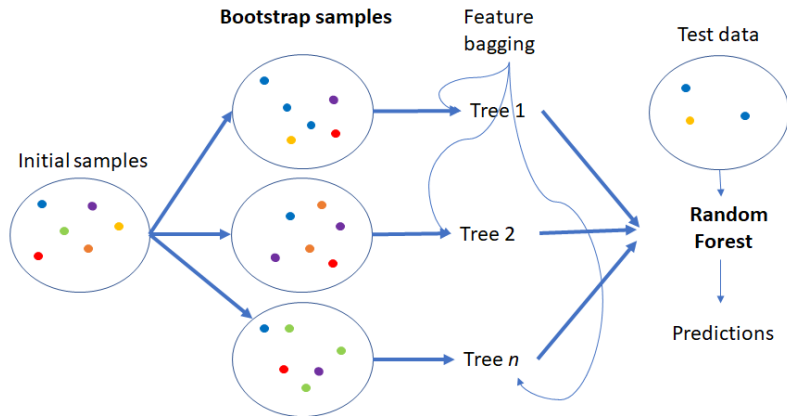


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# Training random forests

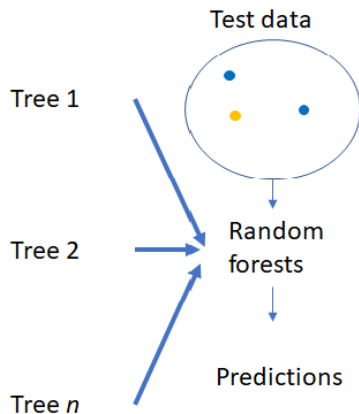
- ▶ The main idea: to train each individual tree to predict the target values well, but to build each tree to be as diverse as possible to the other trees in the same random forest.
- ▶ Why?
- ▶ How?

# Making trees as diverse as possible in random forest



# Making predictions with random forest

- ▶ Make a prediction for every tree in the random forest
- ▶ Then aggregate
  - ▶ for classification: use a majority vote.
  - ▶ for regression: take the mean of all the predictions.



# Random forest algorithm

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**Algorithm 15.1** *Random Forest for Regression or Classification.*

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1. For  $b = 1$  to  $B$ :
  - (a) Draw a bootstrap sample  $\mathbf{Z}^*$  of size  $N$  from the training data.
  - (b) Grow a random-forest tree  $T_b$  to the bootstrapped data, by recursively repeating the following steps for each terminal node of the tree, until the minimum node size  $n_{\min}$  is reached.
    - i. Select  $m$  variables at random from the  $p$  variables.
    - ii. Pick the best variable/split-point among the  $m$ .
    - iii. Split the node into two daughter nodes.
2. Output the ensemble of trees  $\{T_b\}_1^B$ .

To make a prediction at a new point  $x$ :

*Regression:*  $\hat{f}_{\text{rf}}^B(x) = \frac{1}{B} \sum_{b=1}^B T_b(x)$ .

*Classification:* Let  $\hat{C}_b(x)$  be the class prediction of the  $b$ th random-forest tree. Then  $\hat{C}_{\text{rf}}^B(x) = \text{majority vote } \{\hat{C}_b(x)\}_1^B$ .



in scikit-learn

- ▶ `sklearn.ensemble.RandomForestClassifier`
- ▶ `sklearn.ensemble.RandomForestRegressor`
- ▶ Discuss some parameters: `n_estimators`, `max_features`, `random_state`, `n_jobs`.

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# Review of random forests

- ▶ What is the difference between a normal decision tree and a tree within a random forest?
- ▶ What are the positive vs negative aspects of random forests?
- ▶ When is it good/not good to apply random forests?

## Next lecture

- ▶ Preprocessing steps and hyperparameter tuning