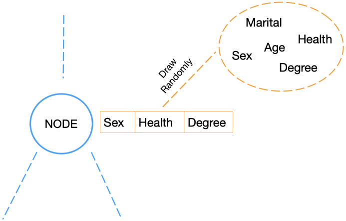
Introduction to Machine Learning

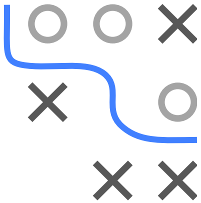
Random Forest
In a Nutshell



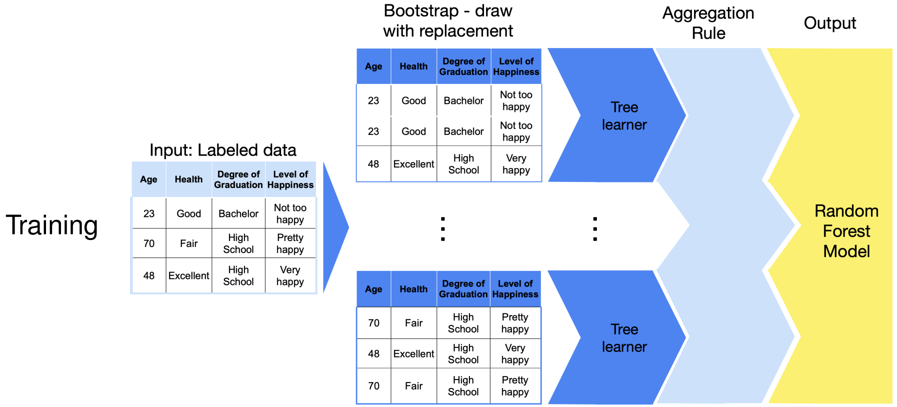
Learning goals

- Understand basic concept of random forest
- Know basic aggregation rules
- Understand concept of feature importance

LEARNING AND PREDICTION WITH RF



- Stabilizes tree learner by bagging (bootstrap aggregation)
- Randomizes tree learner and combines models into one meta model
- Can be adapted to learning task, i.e., classification or regression



Age	Health	Degree of Graduation	Level of Happiness
23	Good	Bachelor	Not too happy
70	Fair	High School	Pretty happy
48	Excellent	High School	Very happy

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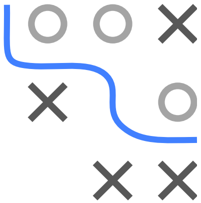
LEARNING AND PREDICTION WITH RF



Prediction

Input: Unlabeled data

Age	Health	Degree of Graduation	Level of Happiness
41	Fair	Bachelor	?
35	Good	Bachelor	?
22	Fair	High School	?

Random Forest Model

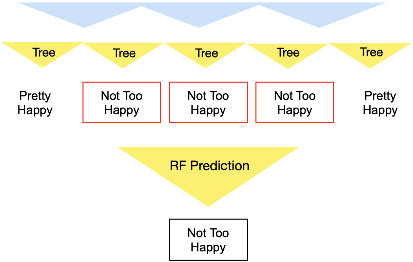
Prediction

Level of Happiness
Not too happy
Pretty happy
Not too happy

AGGREGATION RULES FOR DIFFERENT TASKS

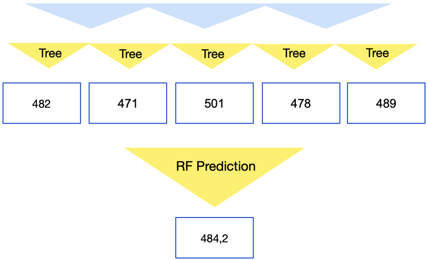
Classification Task - Majority Vote

Age	Health	Degree of Graduation	Level of Happiness
41	Fair	Bachelor	?



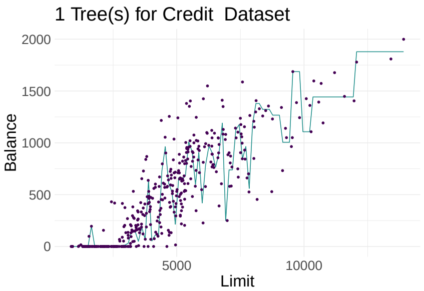
Regression Task - Averaging

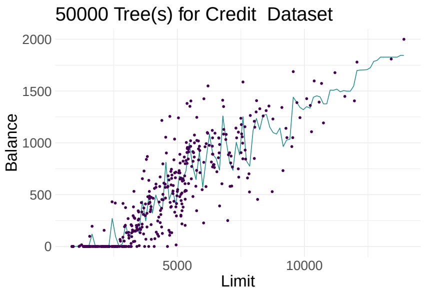
Rating	Income	Credit Limit	Credit Card Balance
107	32.318	4351	?



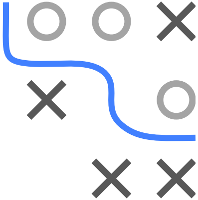
PERFORMANCE OF RF

- In general: Increasing the ensemble size stabilizes the predictions
  - For regression tasks the stabilization is often not sufficient.

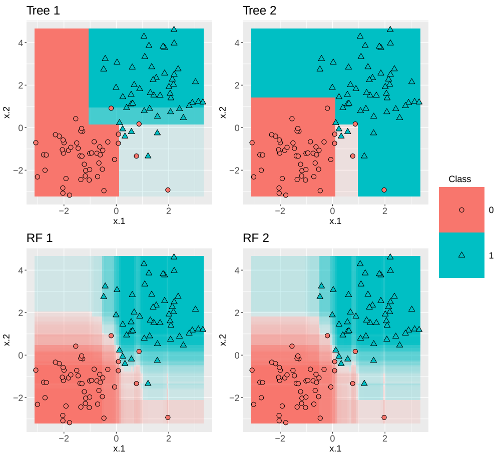




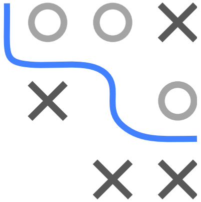
PERFORMANCE OF RF



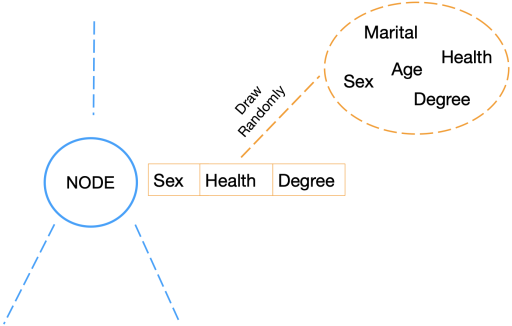
- RF performs well for classification tasks:
  - Two different trees →Quite different decision regions
  - Two different RFs →Similar decision regions



PERFORMANCE OF RF



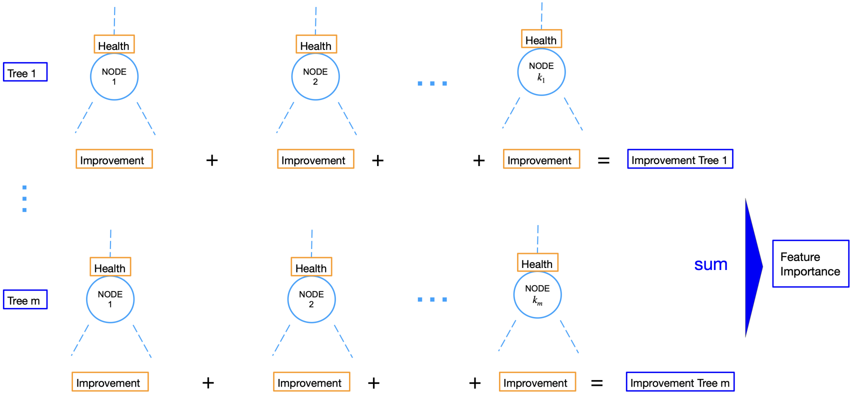
- Trees should be decorrelated, i.e., make mistakes in different directions
- Avoid correlation by
  - Bootstrap sampling
  - Randomized splits. In each node of each tree, consider different features for splitting:



FEATURE IMPORTANCE

Several options, e.g., measure contribution of feature to model:

- Measure based on improvement in splitting criterion
- E.g. Feature importance of 'Health', search all nodes with 'Health' as splitting variable:



FEATURE IMPORTANCE

- Measure based on OOB Loss

Permute

Age	Health	Degree of Graduation	Level of Happiness
23	Fair	Bachelor	Not too happy
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OOB

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Tree 1

⋮

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OOB

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Tree m

Compute OOB Loss for each Observation

Observation i

Age	Health	Degree of Graduation	Level of Happiness
23	Fair	Bachelor	Not too happy

OOB in Tree

Sum

Tree j

Prediction	True Label	Loss
Very happy	Not too happy	0.89

⋮

Tree r

Prediction	True Label	Loss
Pretty happy	Not too happy	0.58

OOB Permutation Loss of Observation i

FEATURE IMPORTANCE

Compute OOB Loss for each Observation

Age	Health	Degree of Graduation	Level of Happiness
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OOB

Tree 1

⋮

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OOB

Tree m

Observation i

Age	Health	Degree of Graduation	Level of Happiness
23	Fair	Bachelor	Not too happy

OOB in Tree

Sum

Tree h

Prediction	True Label	Loss
Pretty happy	Not too happy	0.73

⋮

Tree m

Prediction	True Label	Loss
Not too happy	Not too happy	0.12

OOB Loss of Observation i

Feature Importance ‘Health’ = OOB Permutation Loss of all observations - OOB Loss of all observations