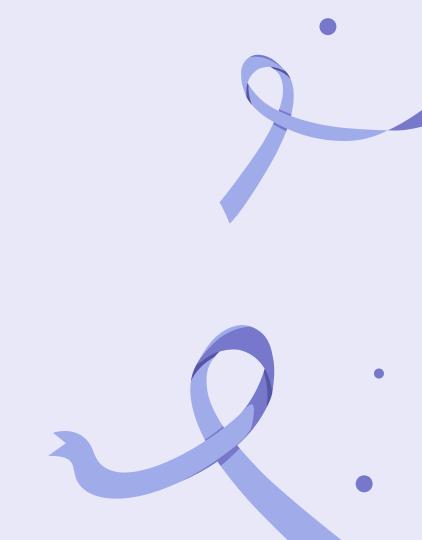


Elínborg Ásbergsdóttir İpek Korkmaz Luca Modica Patrícia Marques

Group 30 Room HC3



02.05.2024



Part 1: Summary

Ensemble Methods

- Bagging (Random Forest)
- Boosting (Gradient Boosting)

Model Parameters

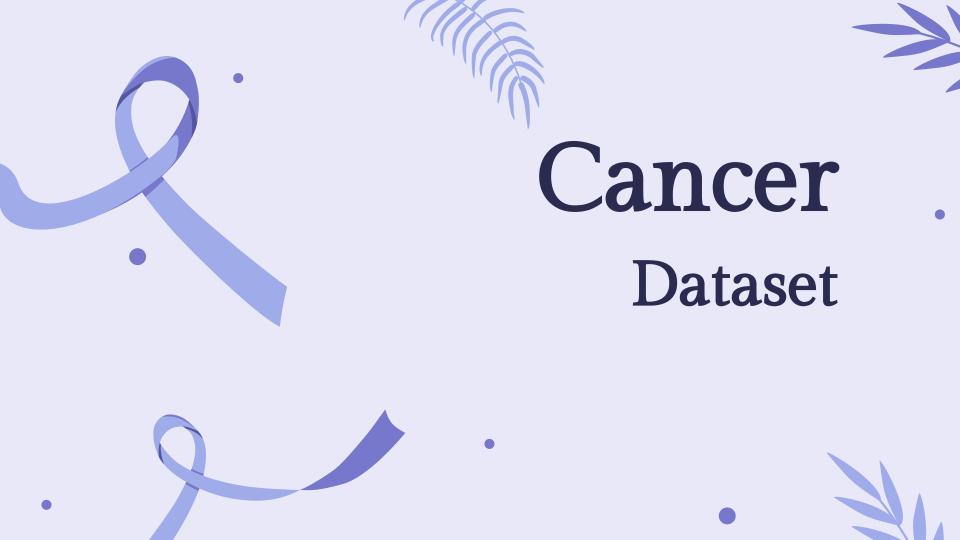
- Number of estimators: 15, 50, 100, 150, 250 (bagging and boosting)
- Maximum depth: None, 3, 5, 10 (bagging and boosting)
- Learning rate: 0.05, 0.1, 0.5 (boosting)

Pipeline

- Standard scaling
- Noise (0%, 30%, 60%, 90%)
- Train (80%) and test (20%) splitting
- Stratified fold splitting (3 folds)

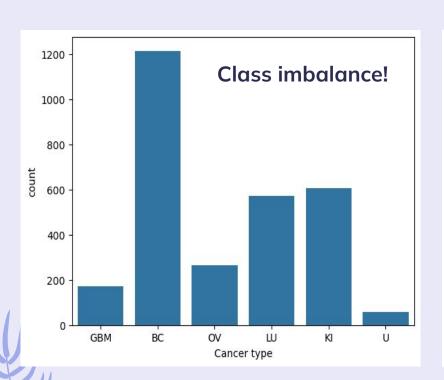
Analysis

• **F1 Score** (cross-validation, train and test)



Cancer dataset exploration

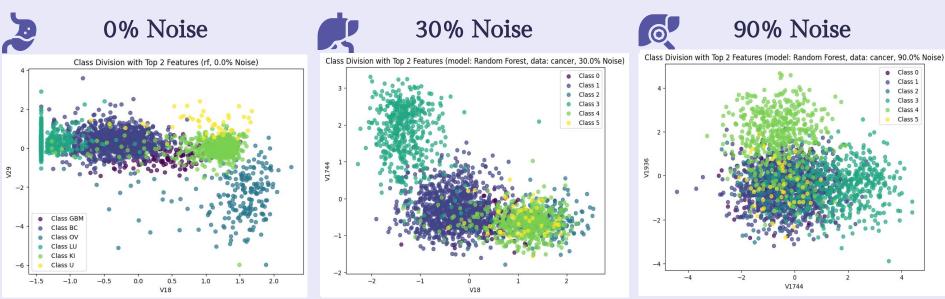












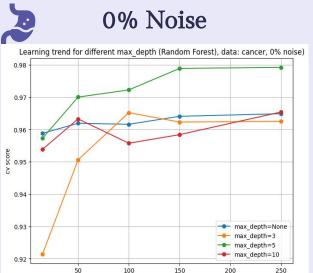
2 features allow to see class **separation**

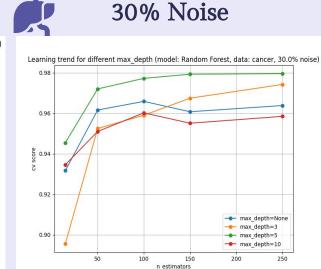
Three classes are **still separable**

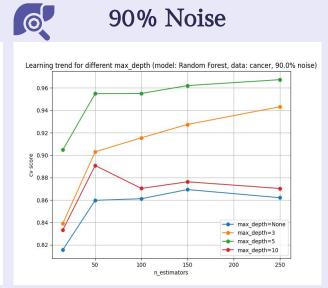
Classes **intertwined** • with only 2 features











A small number of **deep trees** is sufficient

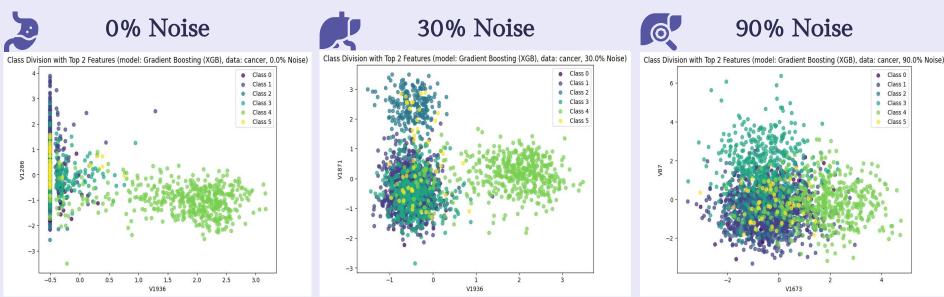
n estimators

Good results especially for **enough estimators**

No benefits from a • depth larger than 5 levels







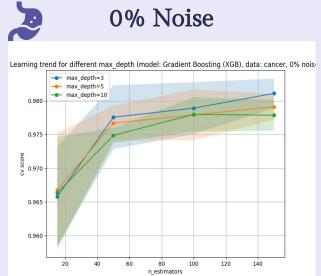
Gene V1936 allows to separate class 4

With only 2 genes some classes are **separable**

No clear **separation** • with only two features

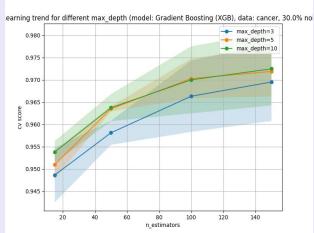
GB: Nr. of Trees and Maximum Depth





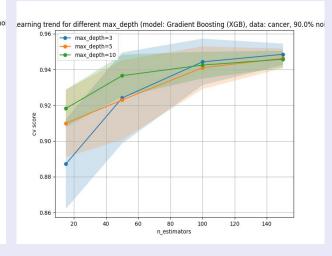


30% Noise





90% Noise



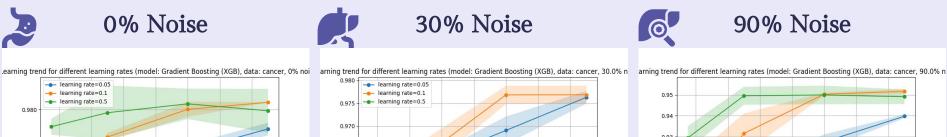
Maximum depth **does not change** F1 score

Results worsen but still good

Similar scores with • enough estimators



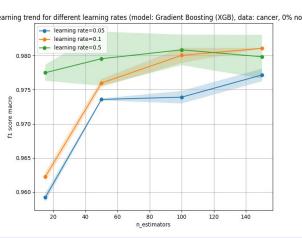


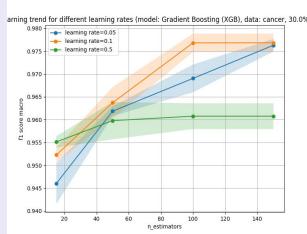


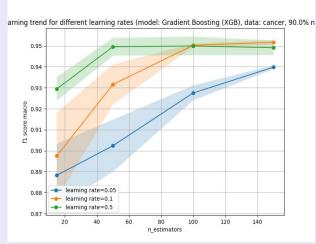




90% Noise





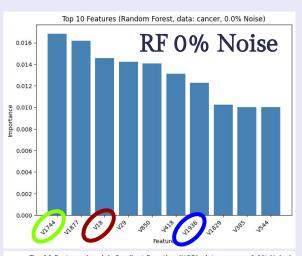


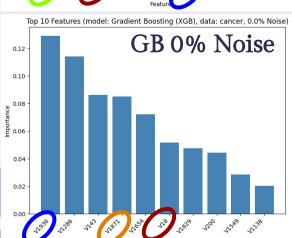
50 trees are enough for large learning rates

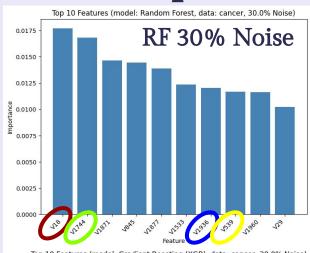
Best results for a small learning rate

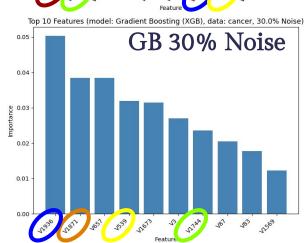
Early stopping effect for small learning rates

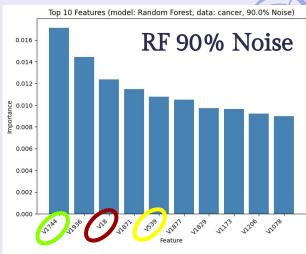
RF vs GB: Top 10 Features

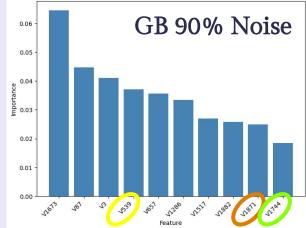




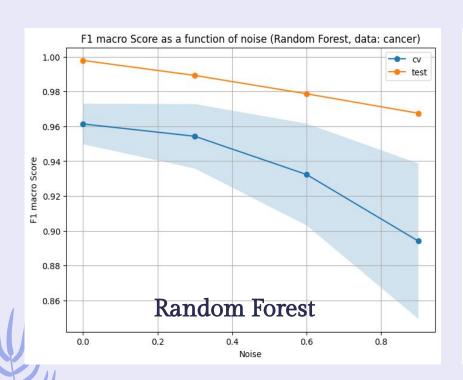


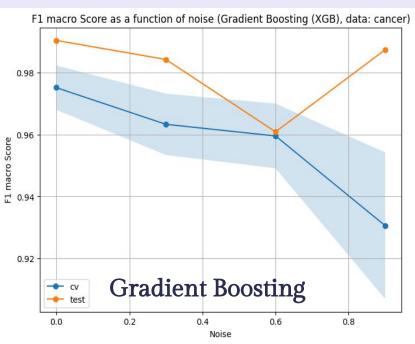






RF vs GB: Performance Comparison







Random Forest: Top Pixels

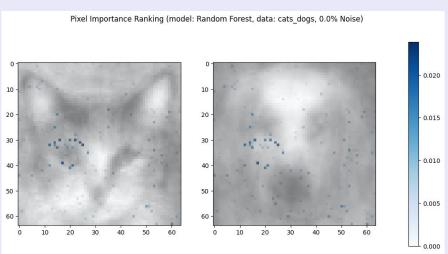


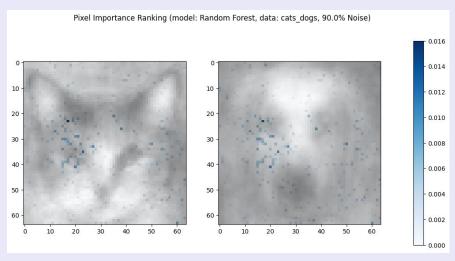


0% Noise



90% Noise





Area of focus around the **cat's eye** and the **dog's cheek**

With noise, **more pixels** gain **importance**





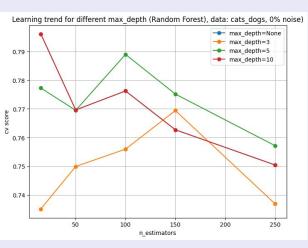


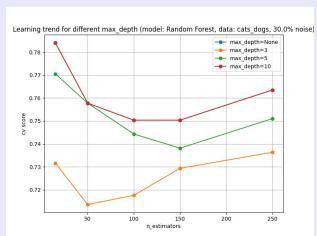


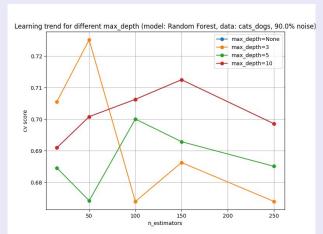
30% Noise



90% Noise







Depths **larger than 3** allow good training

Maximum depth of 10 outperforms

Performance worsens, even with more trees

Gradient Boosting: Top Pixels

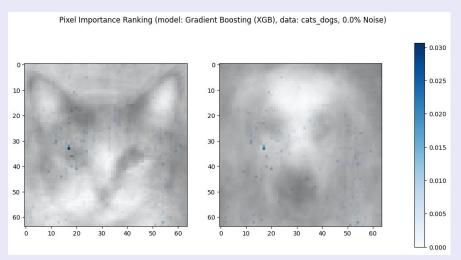


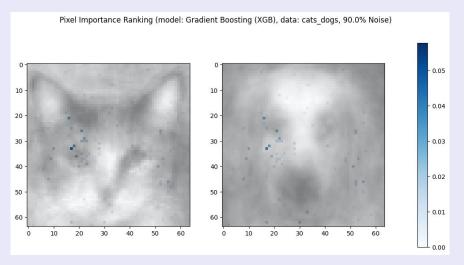


0% Noise



90% Noise





Same area of focus as with RF: around the cat's eye and the dog's cheek

With noise, **maximum** value of importance **increased**





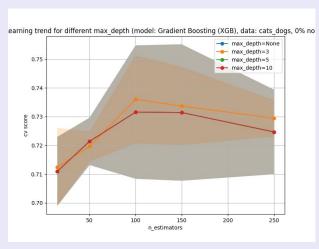


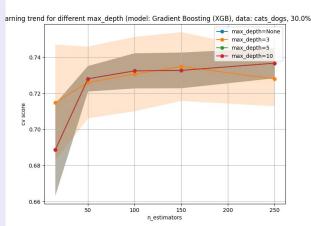


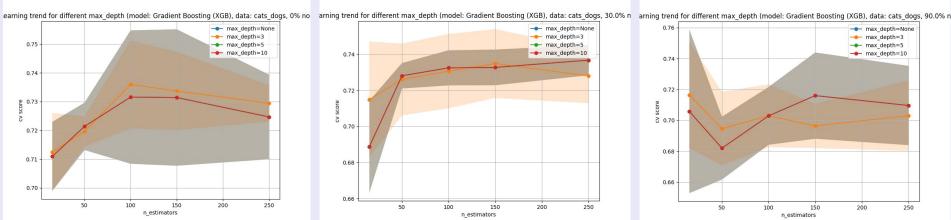
30% Noise



90% Noise









F1 score always below 0.74

Minimal changes for different learning rates **Unstable** F1 scores for all estimators



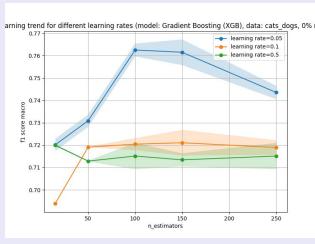


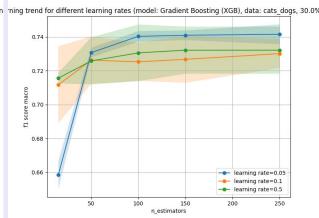


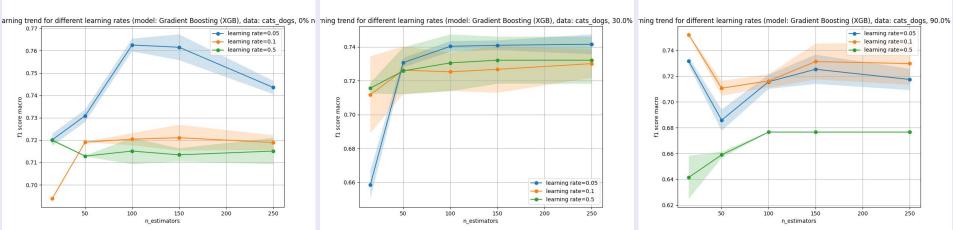




90% Noise





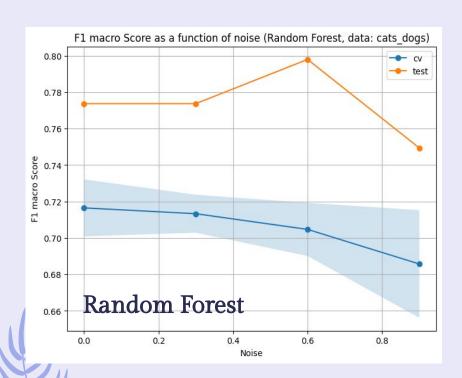


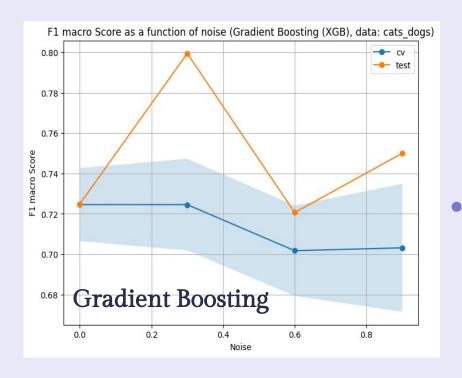
A low learning rate outperforms

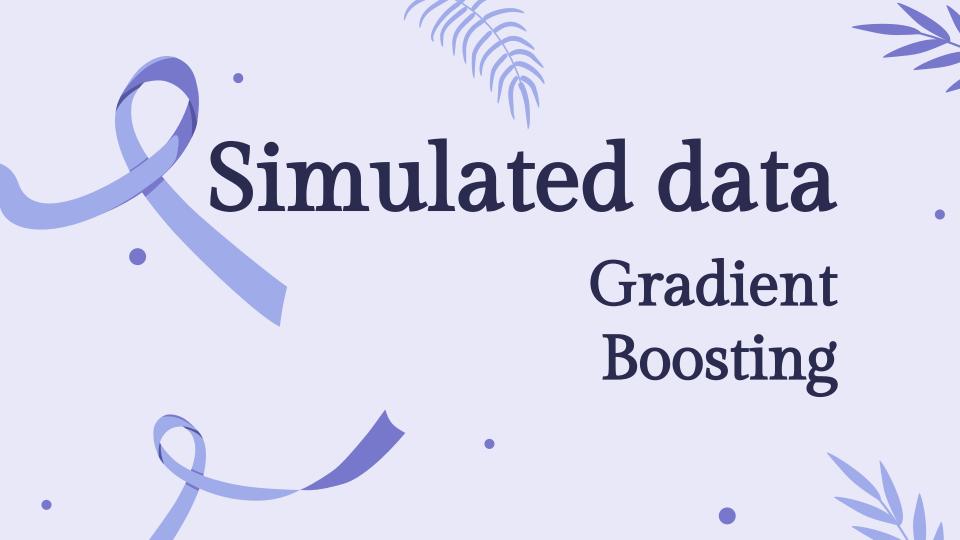
More than 50 trees don't **improve** F1 score clearly

No improvements for • forests with more trees

RF vs GB: Performance Comparison







Part 2: Summary

Simulated dataset

- 400 samples for 400 features:
- 100 informative features
- 3 classes with weights 20%, 30%, 50%
- 70% of class separation

Model Parameters

- Number of estimators: 100 (default)
- Maximum depth: 1, None (default)
- Learning rate: 0.1 (default), 10

Ensemble Method

Boosting (Gradient Boosting)

Procedure

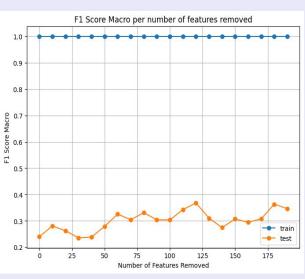
Recursively eliminate features

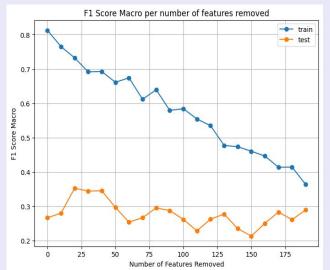
Analysis

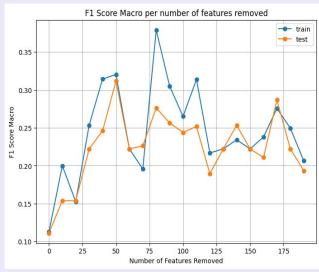
F1 Score



GB: Maximum Depth and Nr. of Trees







Immediate overfitting

Default parameters

Maximum Depth = None

Learning rate = 0.1

Train scores worsen

Shallow decision trees

Maximum Depth = 1

Learning rate = 0.1

Low F1 scores

High learning rate
Maximum depth = None
Learning rate = 10



Does anyone have any questions?

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