



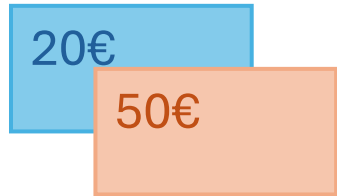
Organisation nationale de lutte contre le  
faux-monnayage

# Counterfeight notes detection based on geometric features

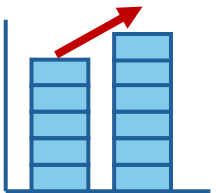
# Euro counterfeiting on the rise



Euro market is well controlled  
18 fake notes per million



Most counterfeit notes are in denominations  
of 20€ and 50€

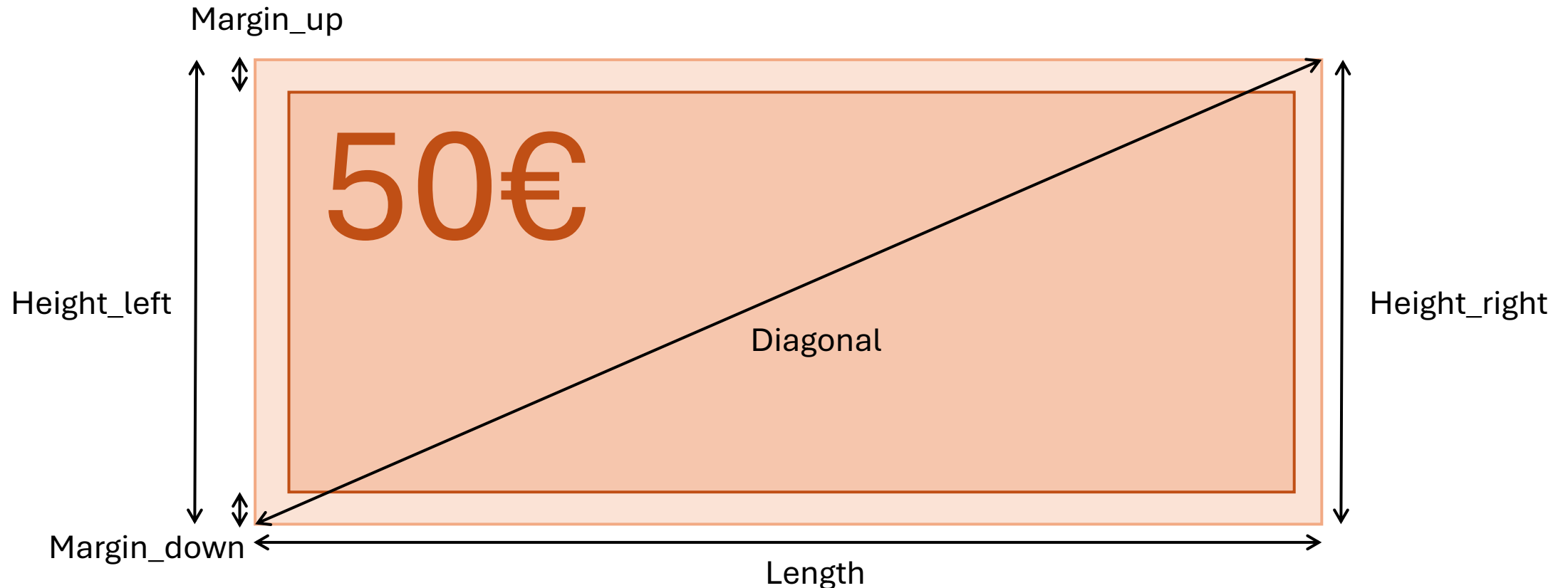


554 000 counterfeit notes seized in 2024  
+20% compared to 2023

- Counterfeiting rise must be controlled now
- We need efficient, scalable methods

# Assess counterfeiting with geometric data

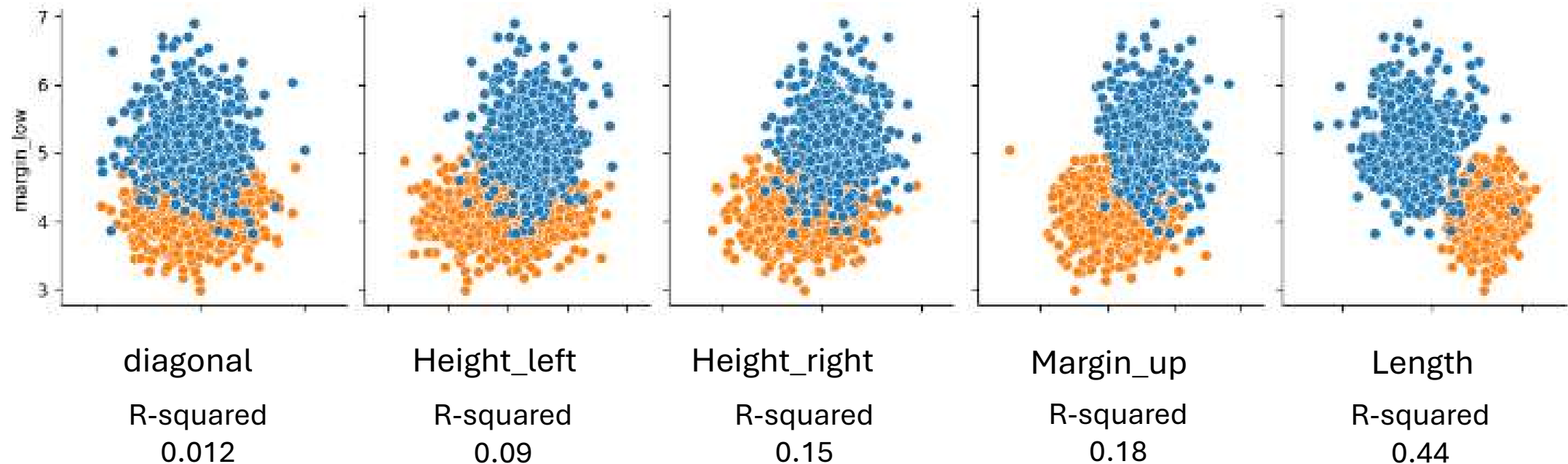
Can we detect fake notes based on geometric data?



# Fill missing values with linear regression

The assumptions of the multiple linear regression are not met

## 1) Linear relationship between dependent and explanatory variables



→ We take the variables with R-squared > 0.1

# Fill missing values with linear regression

The assumptions of the multiple linear regression are not met

## 2) Independence of the residuals: Durbin-Watson statistic

Height\_right

1.18

Positive autocorrelation

Margin\_up

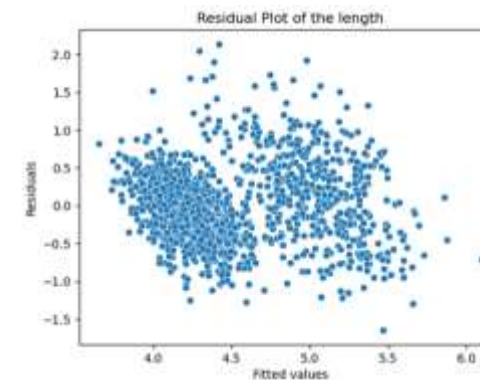
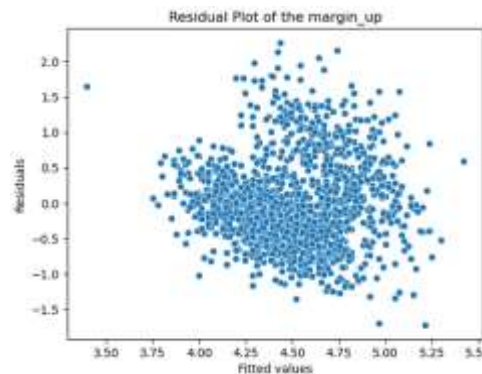
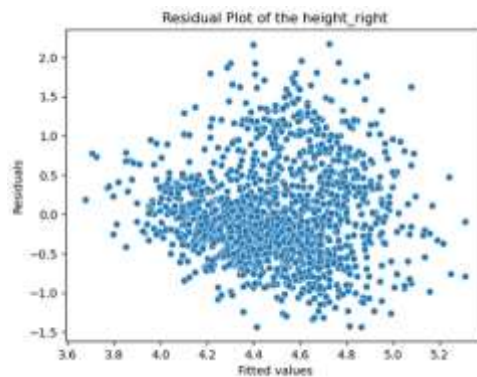
1.32

Positive autocorrelation

Length

1.86

## 3) Homoscedasticity of the residuals

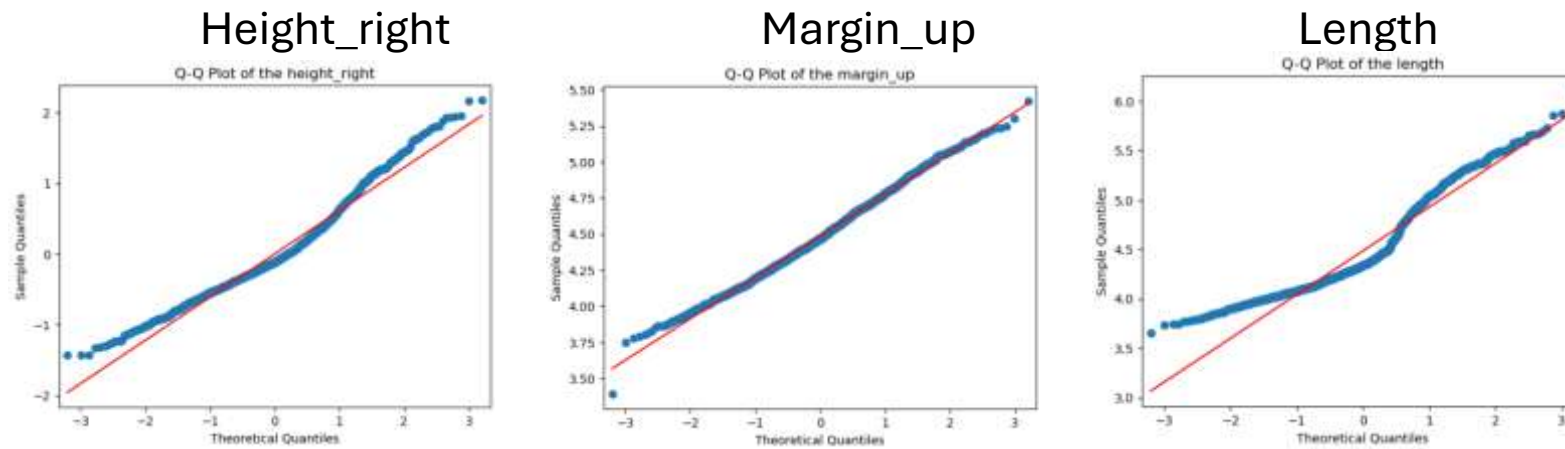


We see clear patterns on every plot

# Fill missing values with linear regression

The assumptions of the multiple linear regression are not met

## 4) Normality of the residuals



The residuals of the length diverge strongly from normality.

## Results

No variable is fit for a linear regression with margin\_low

If we do the linear regression anyway: R-squared = 0.44

**Can we do better?**

# Fill missing values with Random Forest

Default Random Forest cannot be used

## Default parameters results

R-squared on training set: **0.94**

R-squared on validation set: **0.56**



Better than linear regression

Badly overfitted

## Random Forest hyperparameters

Max\_depth

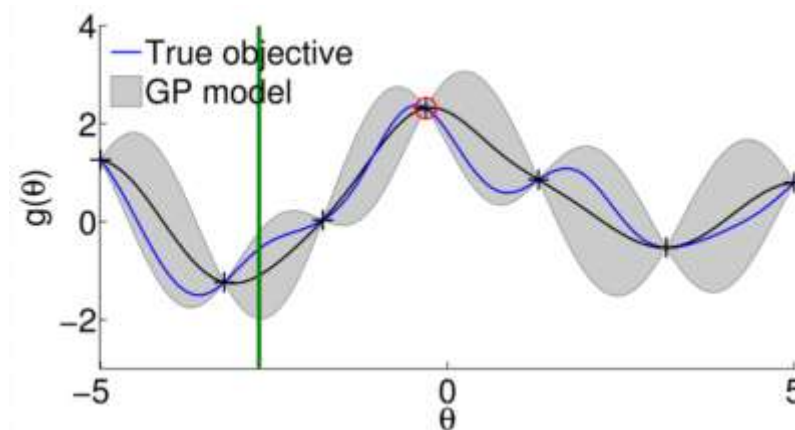
Min\_sample\_leaf

Min\_sample\_split

N\_estimators



## Bayesian search



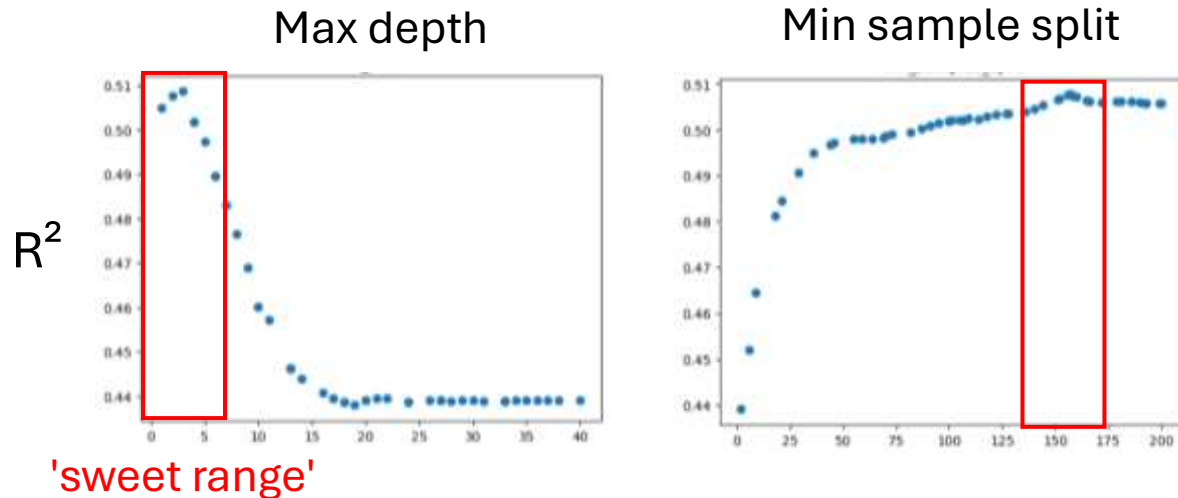
Metric to maximise: R-squared

# Filling data missing values

NA prediction is challenging with both methods, but the RF is better

Bayesian Search in 2 steps

1 – Scan the parameters separately



2 – Scan all parameters over the 'sweet ranges'

Best parameters:  
Max\_depth = 2  
Min\_sample\_leaf = 81  
Min\_sample\_split = 100  
N\_estimators = 100

## Results

R-squared on training set: **0.62**  
R-squared on validation set: **0.62**



Not overfitted  
6% better than before



# Counterfeight notes detection

## List of algorithm tested

### Supervised machine learning

- K-Nearest Neighbors
- Random Forest
- Logistic Regression
- Extreme Gradient Boosting

### "Glassbox" model

- Explainable boosting

### Unsupervised machine learning

- Gaussian Mixture Model

### Accuracy metrics used

$$\textit{Precision} = \frac{TP}{TP + FP}$$

Higher values reduces false positives.

$$\textit{Recall} = \frac{TP}{TP + FN}$$

Higher values reduces false negatives.

$$\textit{F1} = 2 * \frac{\textit{Precision} * \textit{Recall}}{\textit{Precision} + \textit{Recall}}$$

Balances precision and recall.

Used for model optimisation

# Optimization strategy for each model type

## **Supervised machine learning**

Hyperparameter tuning  
(2-step Bayesian Search)

## **Explainable boosting**

## **Gaussian Mixture Model**

Define number of clusters

### **Model fitness**

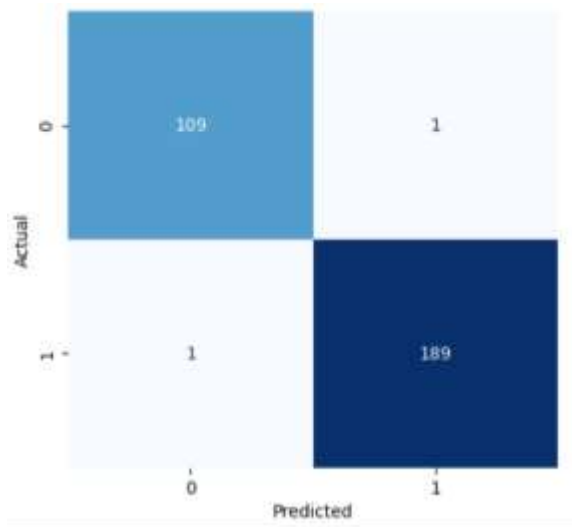
Cluster ID interpretation

### **Accuracy assessment**

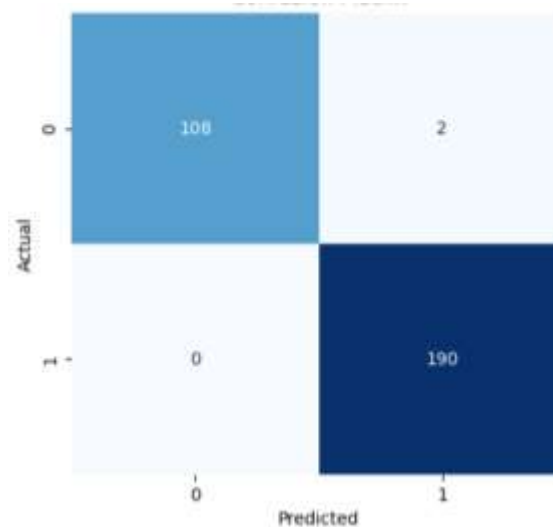
F1 of training set vs F1 of validation set  
Confusion matrix

# Confusion matrices for each model

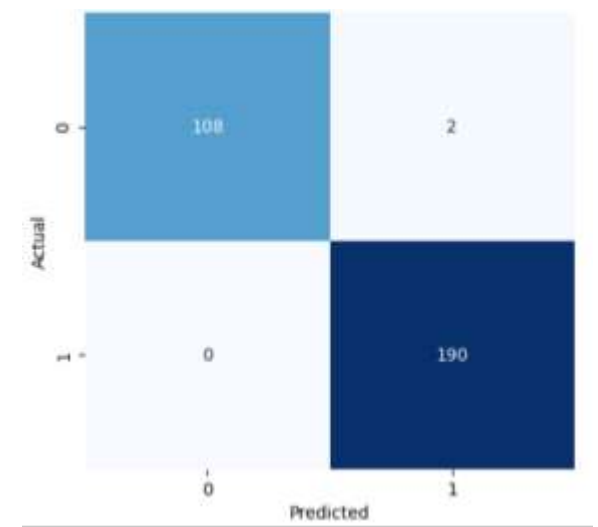
KNN



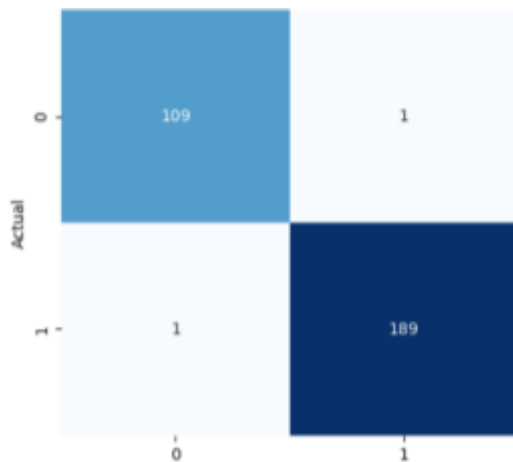
Random Forest



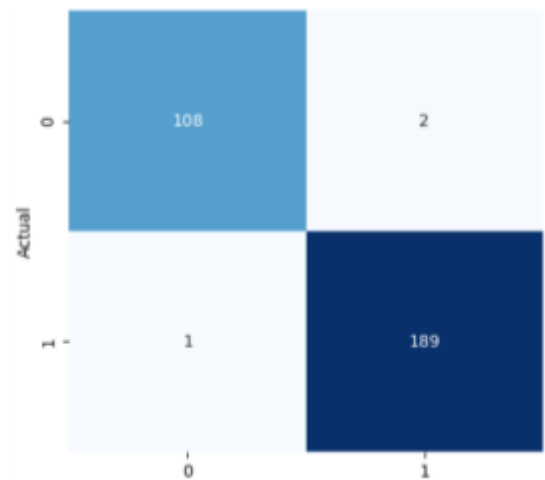
Logistic regression



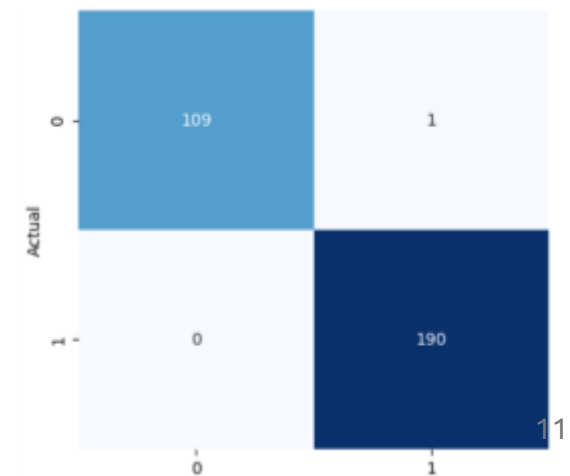
XGBoost



Explainable boosting

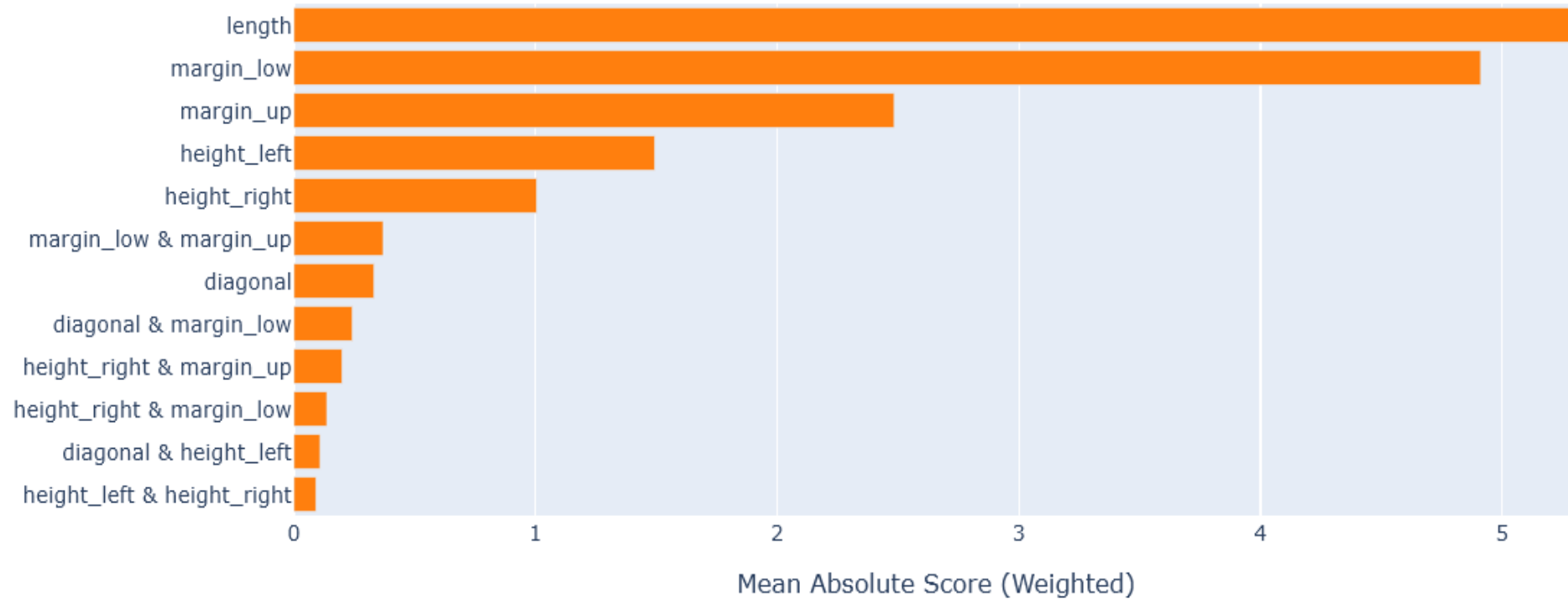


Gaussian Mixture Model



# Relative importance of each parameter

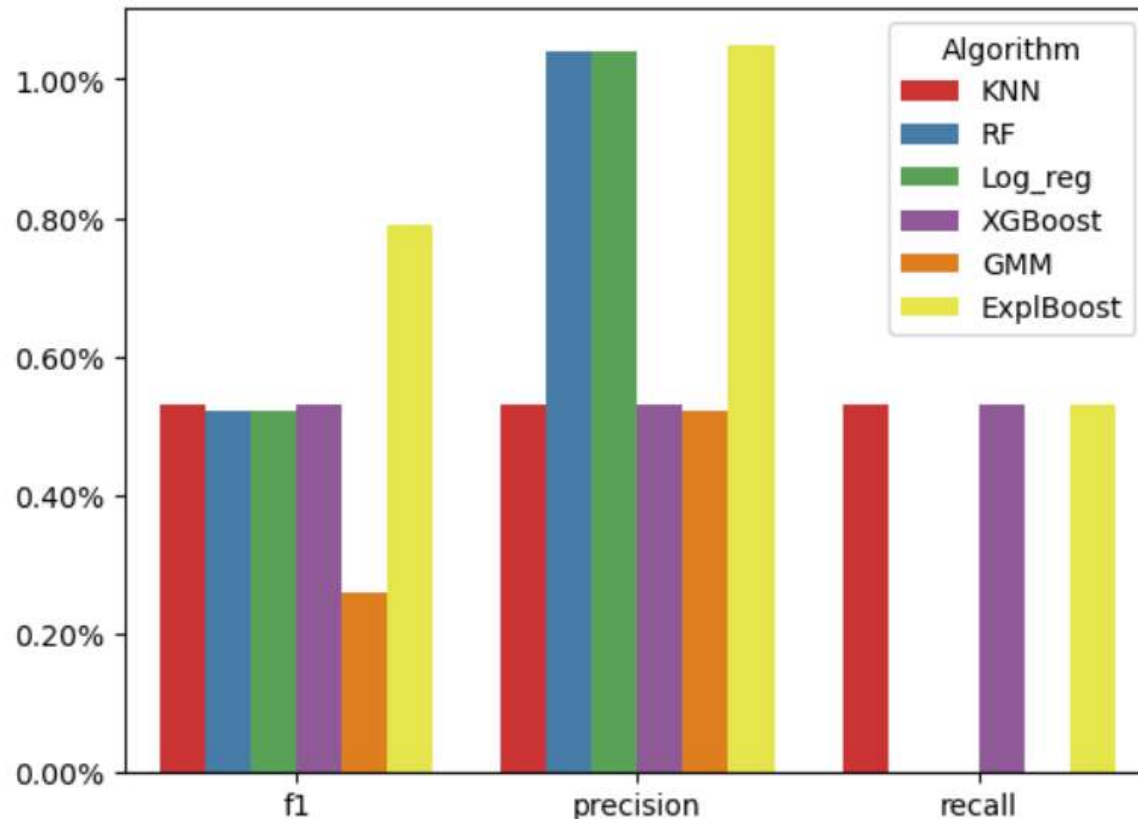
The length and margin\_low are by far the most important predictive variables



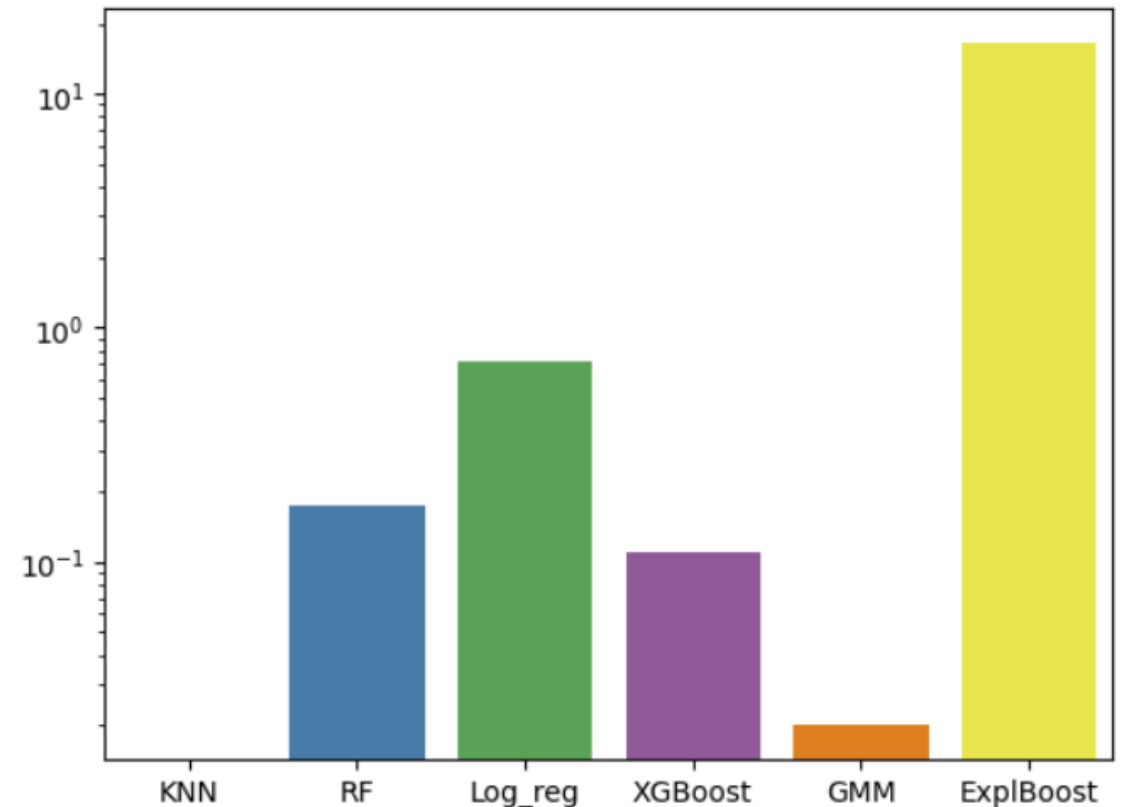
# Model comparison

The Gaussian Mixture Model is very fast and accurate

Inaccuracy of the model (1 - metric)



Fitness time in seconds



Thank you for your attention