RESEARCH OF BOOSTING ALGORITHMS VERSUS TRADITIONAL METHODS IN CREDIT CARD FRAUD DETECTION ACROSS VARIED DATASETS

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Why This Research Matters

- Addressing a Major Challenge: Credit card fraud poses a significant financial threat.
- Advanced Solutions: Tests boosting algorithms known for superior performance.
- Practical Impact: Provides data-driven insights to enhance fraud detection systems, adapting to evolving fraud tactics.

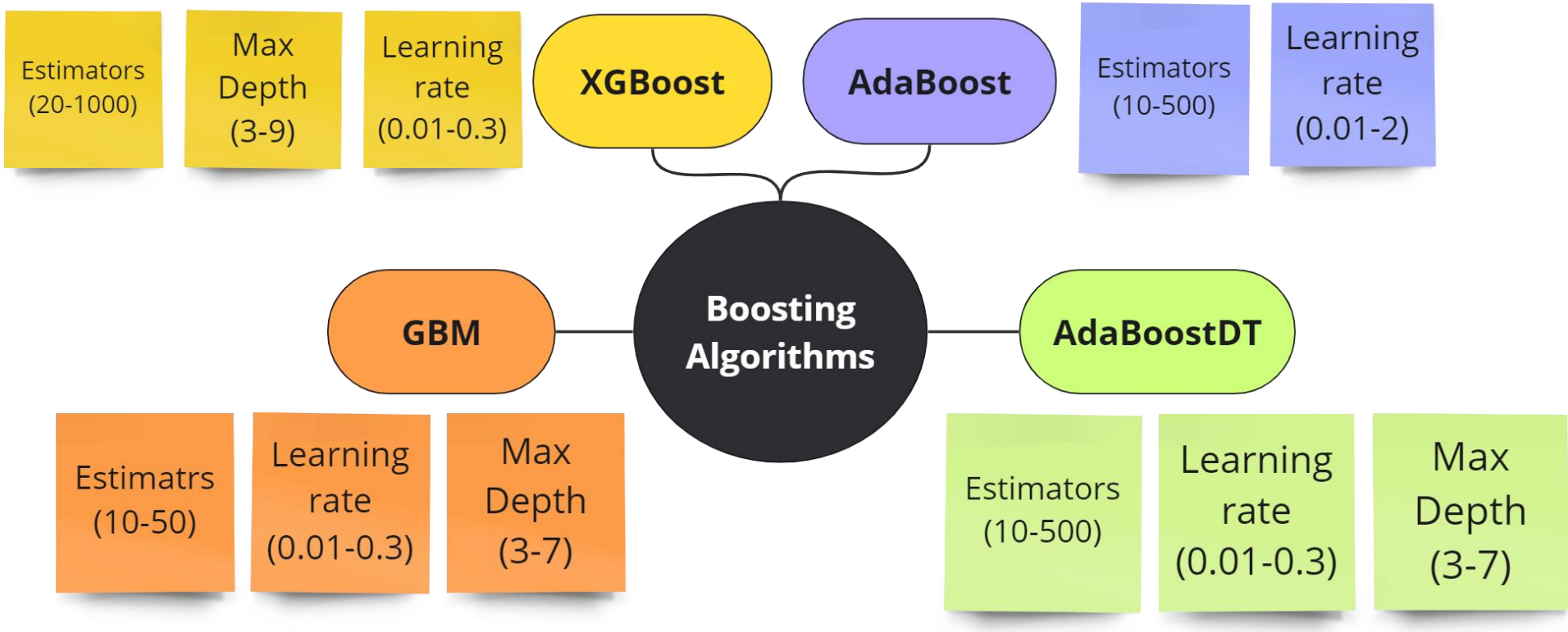
Objectives

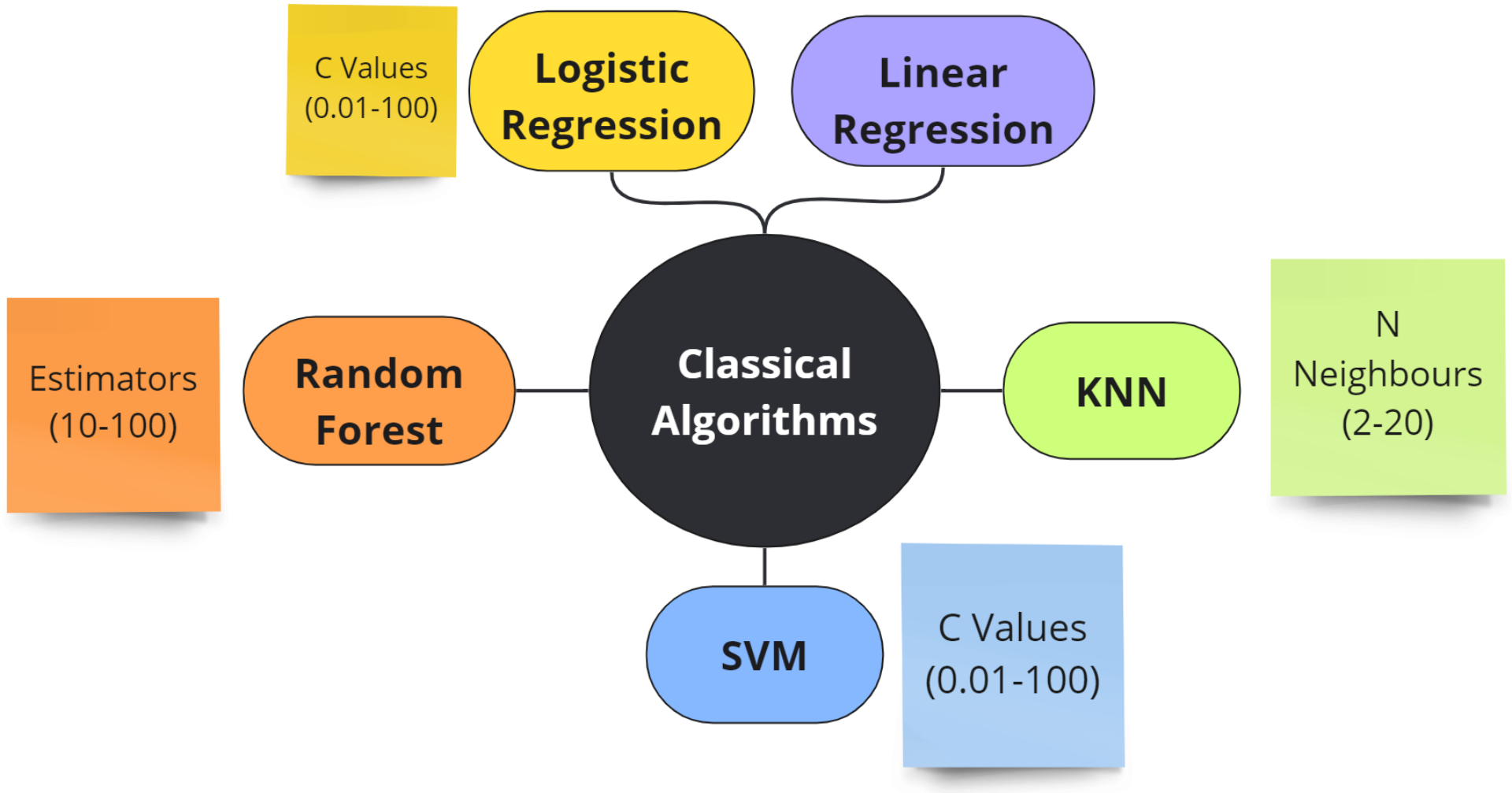
- Goal: Evaluate and compare the effectiveness of boosting algorithms
- Objective: Assess multiple machine learning approaches across three distinct datasets: synthetic, balanced, and highly unbalanced
- Key insights: Determine the best-performing algorithms based on F1 score, accuracy, precision, recall to optimize fraud detection strategies

Outline

- Algorithms tested
- Datasets
- Implementation
- Algorithm performance analysis
- Conclusions

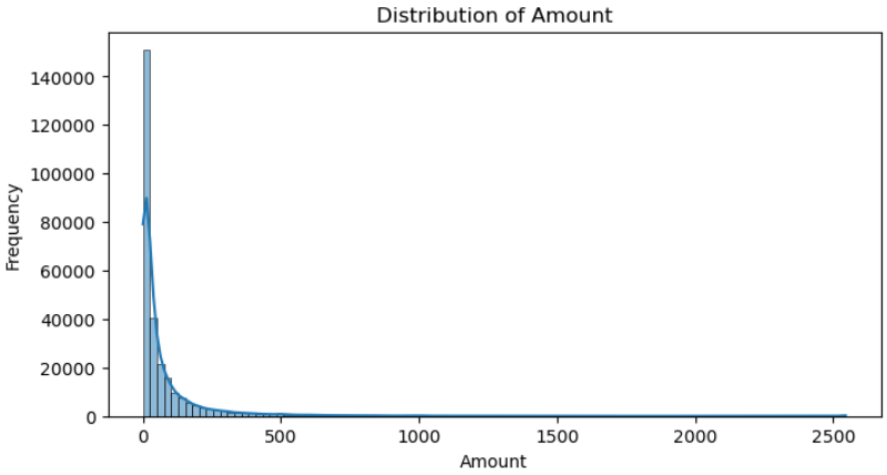
Algorithms tested

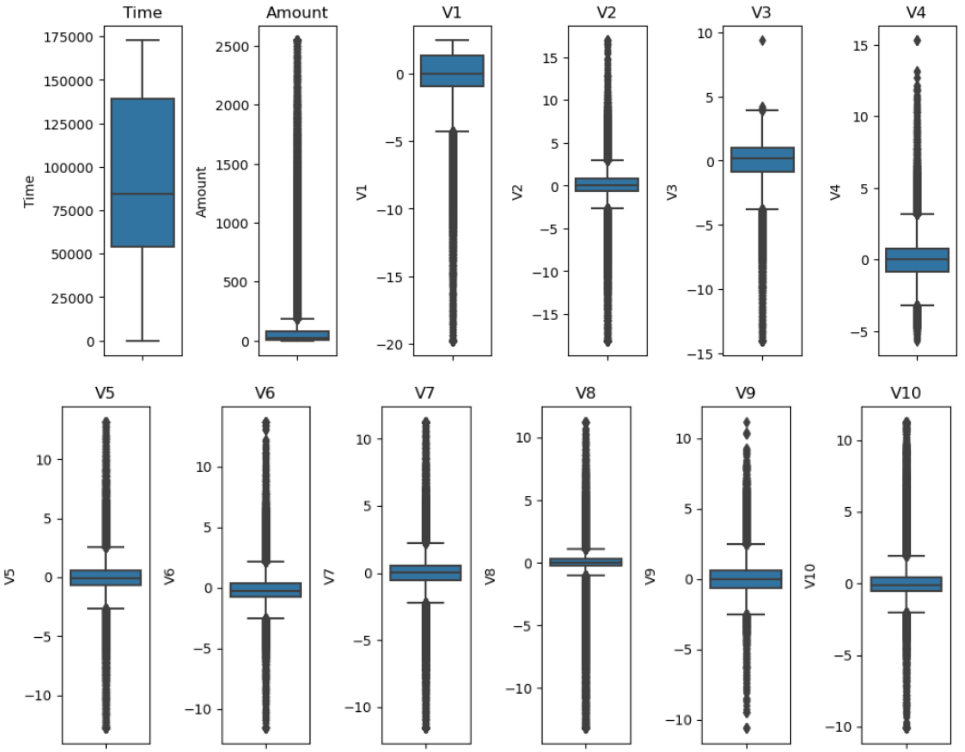



C Values
(0.01-100)
Logistic Regression
Linear Regression
Estimators
(10-100)
Random Forest
Classical Algorithms
KNN
N
Neighbours
(2-20)
SVM
C Values
(0.01-100)

Datasets

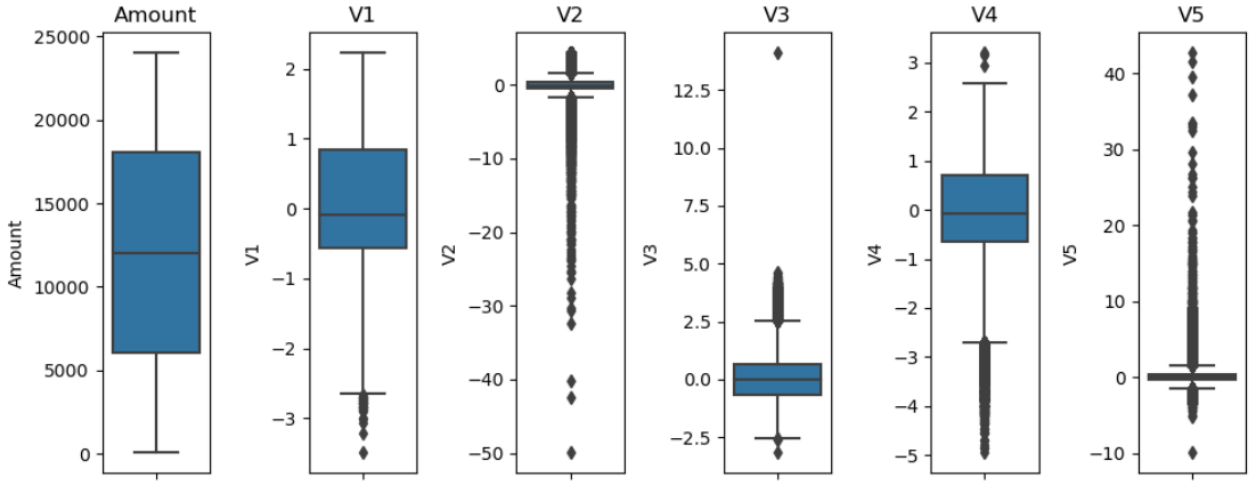
- **Unballanced** dataset: 284k rows, 30 features, 492 fraud cases (0.17%). All features exept time and transaction amount are anonymized using PCA. Source: Kaggle (2018) *transactions made by European cardholders in September 2013*

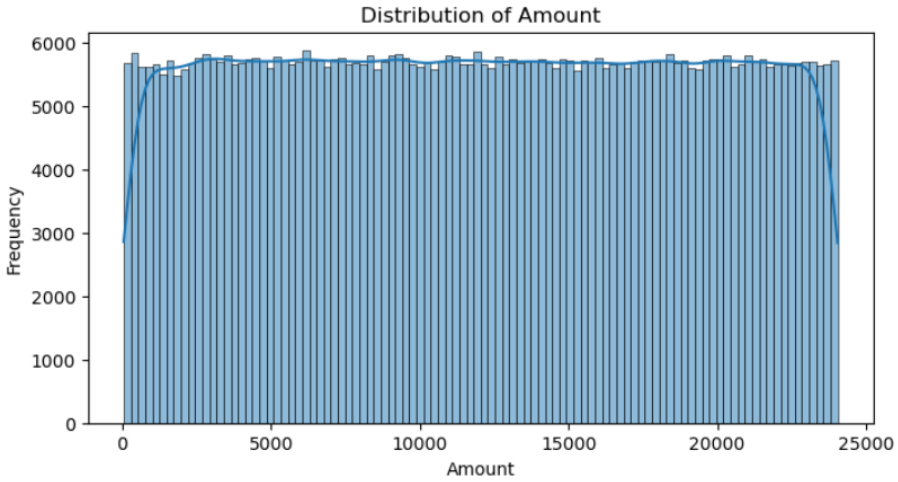


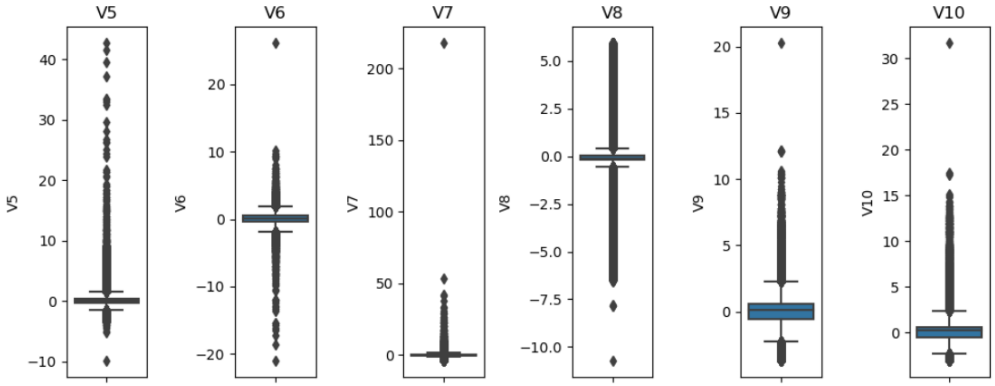


- **Ballanced** dataset: 568k rows, 29 features, 280k fraud cases (50%).

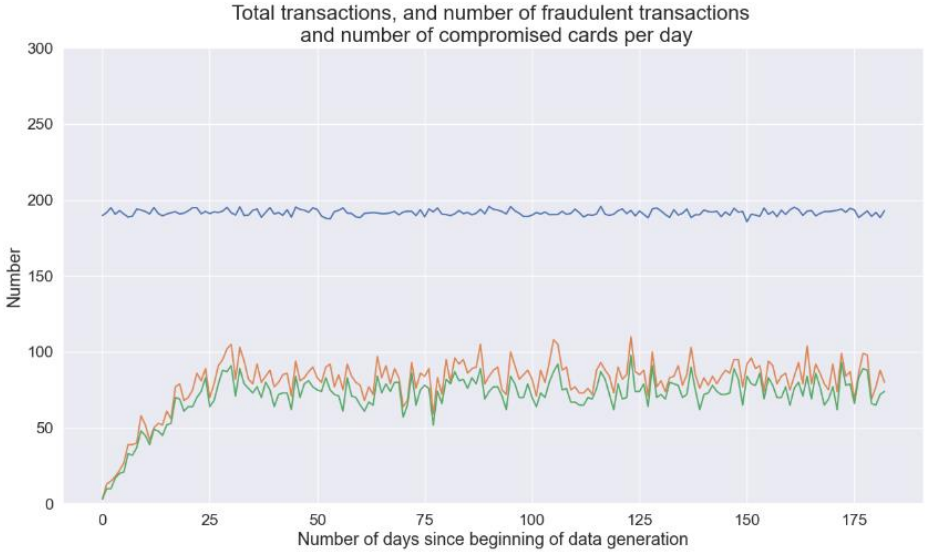
Source: Kaggle (2023). Transactions made by European cardholders in 2023

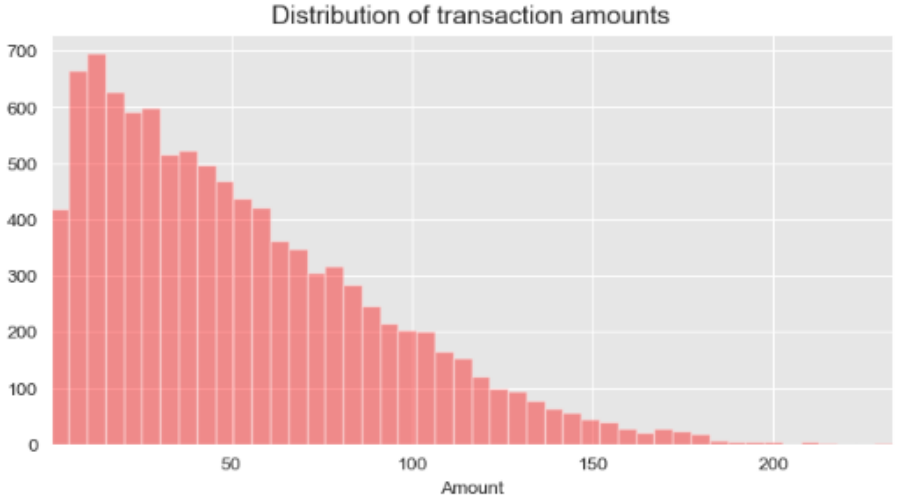


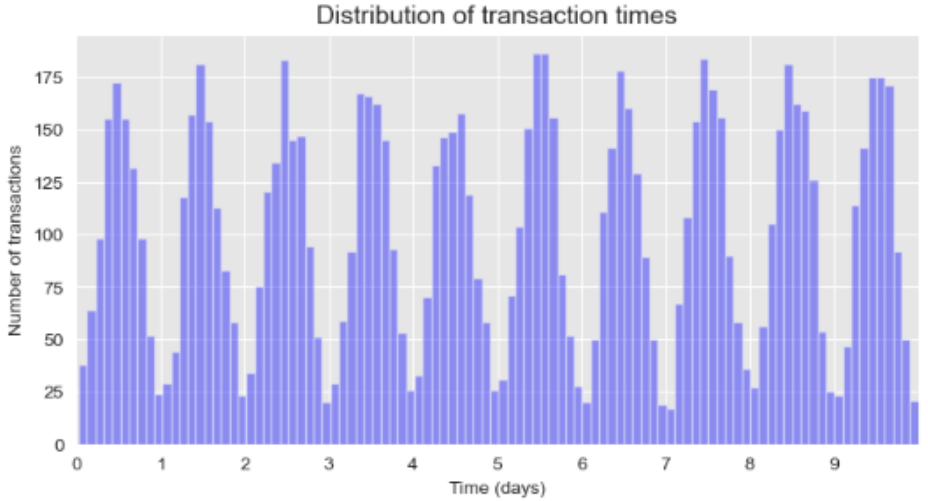




- **Synthetic** data: Generated with python script, 1.7m rows, 5 features, 14k fraud cases (0.84%)







Implementation

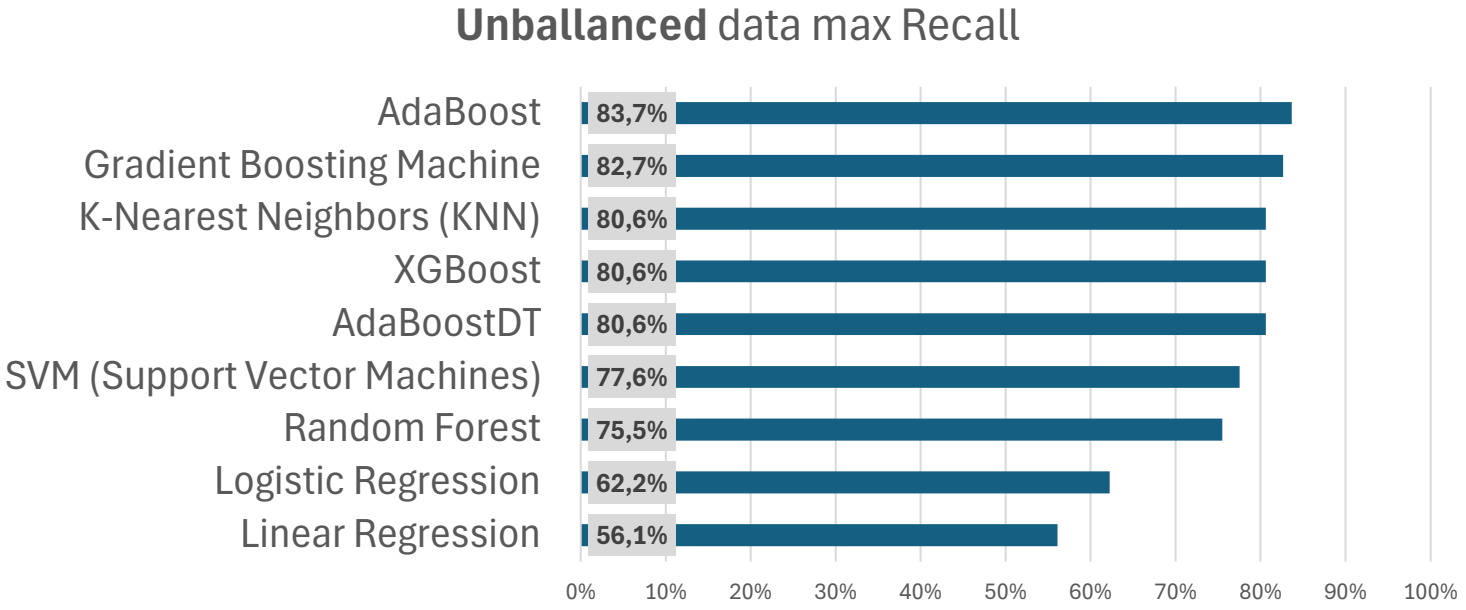
- Tools: Python notebooks, Excel
- Preprocessing: Data cleaning and preparation for modeling
- Parameter tuning: In total 900 semi-automated tests were done
- Testing environment: Laptop
  - 10 Core 12th gen Intel CPU
  - 16 GB RAM

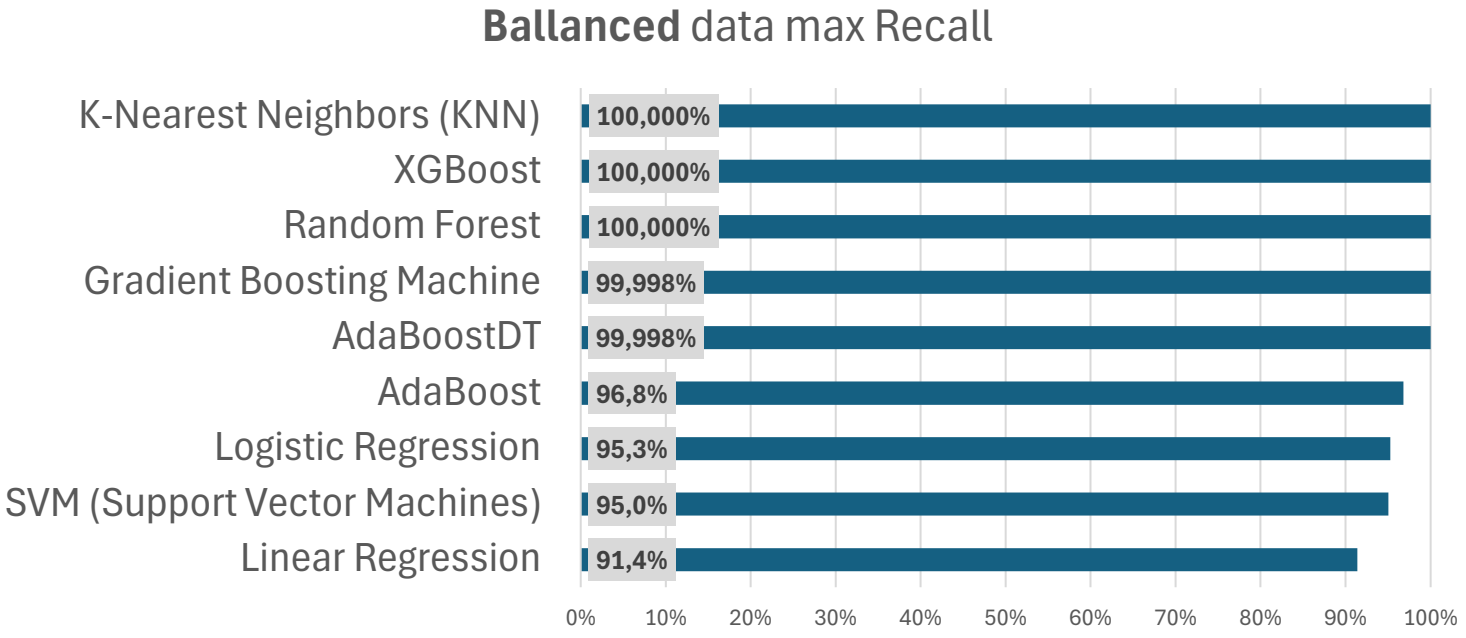
Algorithm performance analysis

Why each metric was chosen for tests:

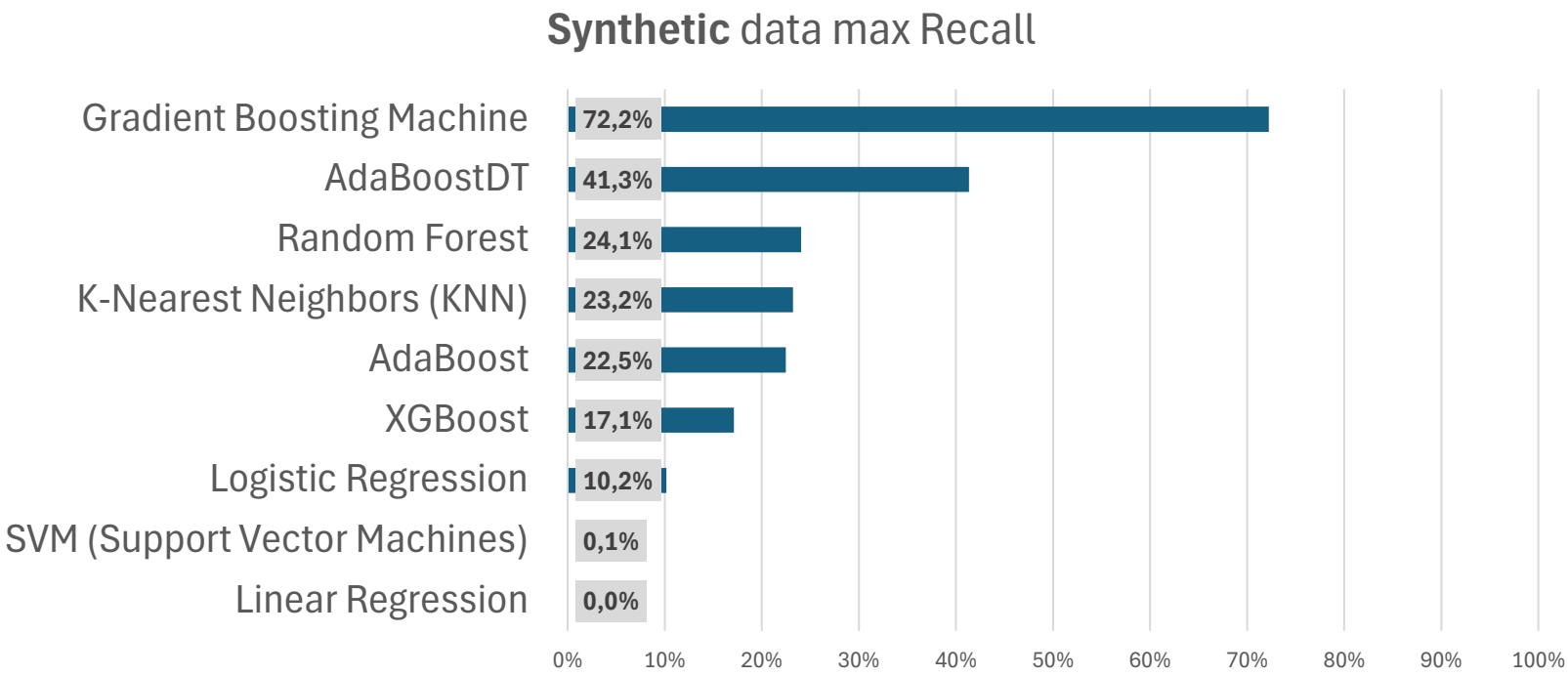
- **Recall** when it is critical to catch as many frauds as possible (minimizing false negatives)
- **Precision** when it is crucial to be as accurate as possible in your fraud predictions (minimizing false positives)
- **F1 Score** when you need a balance between precision and recall, and both types of errors are similarly costly
- **Accuracy** only when the classes are somewhat balanced or when you want a general idea of the model's performance across all predictions

Recall


Unballanced data max Recall
AdaBoost
Gradient Boosting Machine
K-Nearest Neighbors (KNN)
XGBoost
AdaBoostDT
SVM (Support Vector Machines)
Random Forest
Logistic Regression
Linear Regression
83,7%
82,7%
80,6%
80,6%
80,6%
77,6%
75,5%
62,2%
56,1%
0%
10%
20%
30%
40%
50%
60%
70%
80%
90%
100%


Ballanced data max Recall
K-Nearest Neighbors (KNN)
XGBoost
Random Forest
Gradient Boosting Machine
AdaBoostDT
AdaBoost
Logistic Regression
SVM (Support Vector Machines)
Linear Regression
100,000%
100,000%
100,000%
99,998%
99,998%
96,8%
95,3%
95,0%
91,4%
0%
10%
20%
30%
40%
50%
60%
70%
80%
90%
100%

Recall


Synthetic data max Recall
Gradient Boosting Machine
AdaBoostDT
Random Forest
K-Nearest Neighbors (KNN)
AdaBoost
XGBoost
Logistic Regression
SVM (Support Vector Machines)
Linear Regression
72,2%
41,3%
24,1%
23,2%
22,5%
17,1%
10,2%
0,1%
0,0%
0%
10%
20%
30%
40%
50%
60%
70%
80%
90%
100%

Accuracy

	Max of Accuracy		
	Unballanced	**Ballanced**	**Synthetic**
XGBoost	99,96%	99,99%	99,26%
AdaBoostDT	99,96%	99,98%	99,50%
Random Forest	99,96%	99,99%	99,38%
K-Nearest Neighbors (KNN)	99,95%	99,93%	99,36%
AdaBoost	99,95%	97,62%	99,37%
Gradient Boosting Machine	99,95%	99,96%	99,60%
SVM (Support Vector Machines)	99,94%	96,39%	99,19%
Logistic Regression	99,92%	96,53%	99,27%
Linear Regression	99,91%	94,84%	99,19%

F1 Score

	Max of F1 Score		
	Unballanced	**Ballanced**	**Synthetic**
XGBoost	88,27%	99,99%	26,86%
AdaBoostDT	87,64%	99,98%	57,55%
Random Forest	85,55%	99,99%	38,74%
K-Nearest Neighbors (KNN)	85,39%	99,93%	36,02%
AdaBoost	85,08%	97,61%	36,72%
Gradient Boosting Machine	82,76%	99,96%	72,04%
SVM (Support Vector Machines)	82,16%	96,34%	0,21%
Logistic Regression	72,62%	96,49%	18,47%
Linear Regression	67,48%	94,67%	0,07%

Precision

	Max of Precision		
	Unballanced	**Ballanced**	**Synthetic**
Random Forest	100,0%	100,0%	99,6%
Gradient Boosting Machine	100,0%	99,9%	100,0%
XGBoost	98,7%	100,0%	100,0%
AdaBoostDT	98,7%	100,0%	100,0%
K-Nearest Neighbors (KNN)	95,0%	99,9%	99,2%
AdaBoost	92,8%	98,5%	100,0%
SVM (Support Vector Machines)	89,2%	98,1%	100,0%
Logistic Regression	87,1%	98,2%	100,0%
Linear Regression	84,6%	98,2%	100,0%

Conclusions

- For Fraud detection in real world scenarious AdaBoost has best performance from tested algorithms, and outperforms other Boosting and classical algorithms
- Other algorithms perform better in different situations which is interesting for other industries where Accuracy, F1 Score or Precision would be more important
- Gradient Boosting Machine might be go to algorithm with uncertain or changing data, as it performed well on both, real and synthetic data

Acknowledgements

- The research was supervised by Dr.sc.ing., Professor Nadezda Spiridovska, whose insights and guidance were invaluable throughout the study

Thank you

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