Banking Customer Churn Prediction

Artificial Intelligence – Supervised Learning

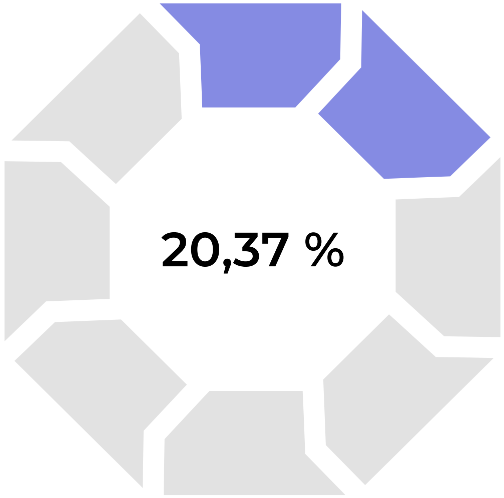
Banking Customer Churn Prediction

Dataset

Bank customers and their churn status, which indicates whether they have exited the bank or not.

Machine learning problem

Factors influencing customer churn in banking institutions and build predictive models to identify customers at risk of churning.



Churn rate : 2037 / 10000

Tools and algorithms to use

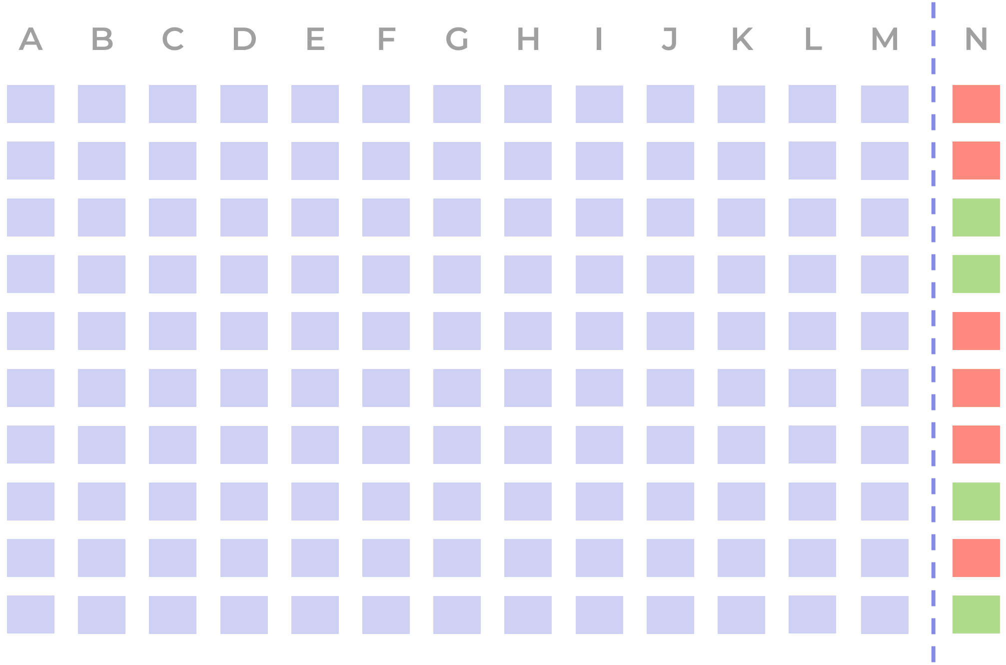
Tools

- Pandas
- Numpy
- MatPlot
- Seaborn
- Scikit-learn
- TensorFlow
- Imbalanced-learn

Algorithms

- Decision Trees
- Neural Networks
- K-Nearest Neighbors (K-NN)
- Support Vector Machines (SVM)
- Naïve Bayes

Dataset features



A : row number

B : customer id

C : surname

D : credit score

E : geography

F : gender

G : age

H : tenure

I : balance

J : numOfProducts

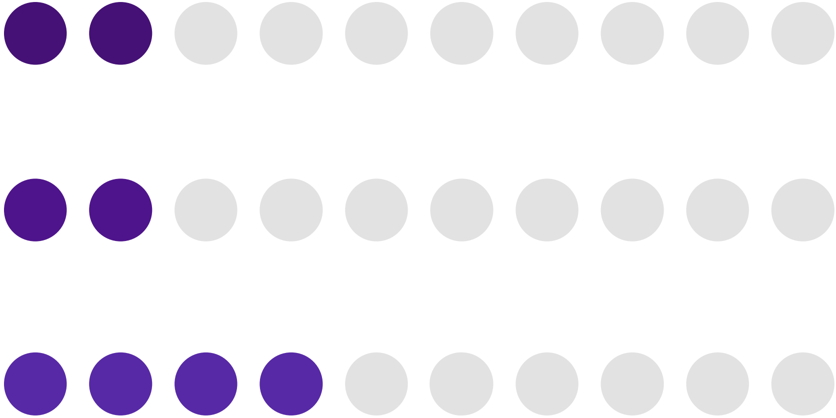
K : hasCreditCard

L : isActiveMember

M : estimatedSalary

N : exited

Exited customers per country



16% **Spain**

Churn rate : 413 / 2477

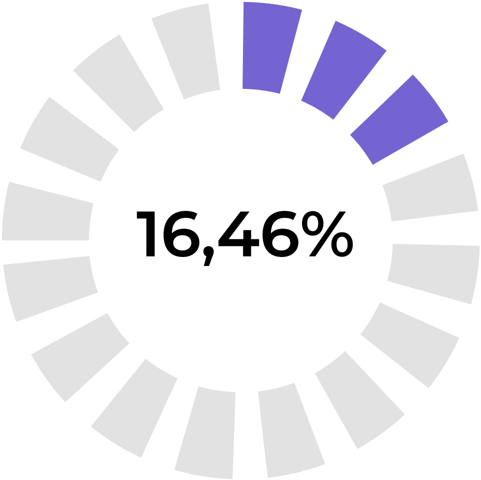
16% **France**

Churn rate : 810 / 5014

32% **Germany**

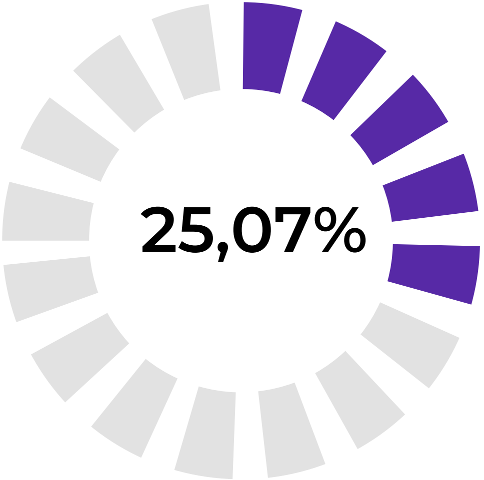
Churn rate : 814 / 2509

Exited customers per gender



Male

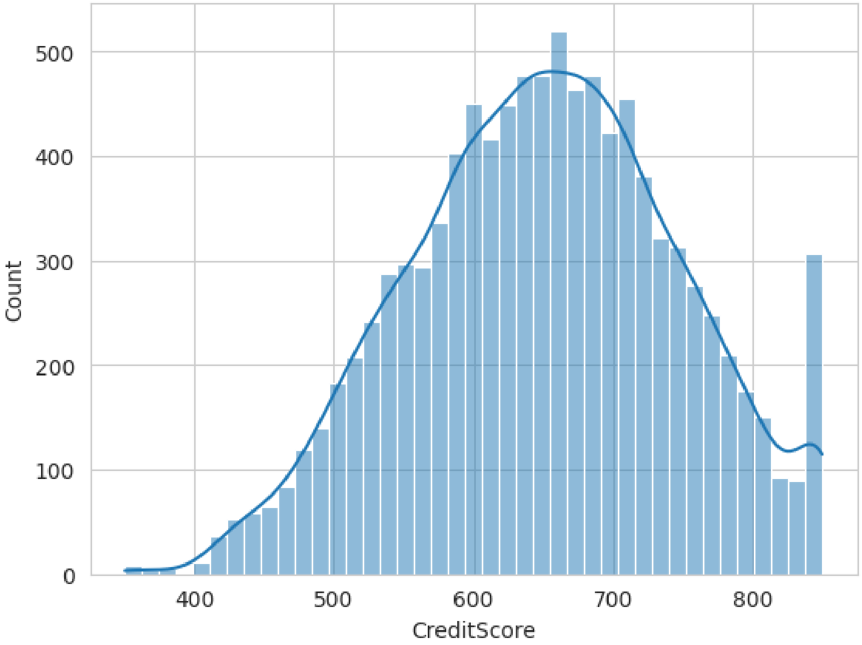
Churn rate : 898 / 5457

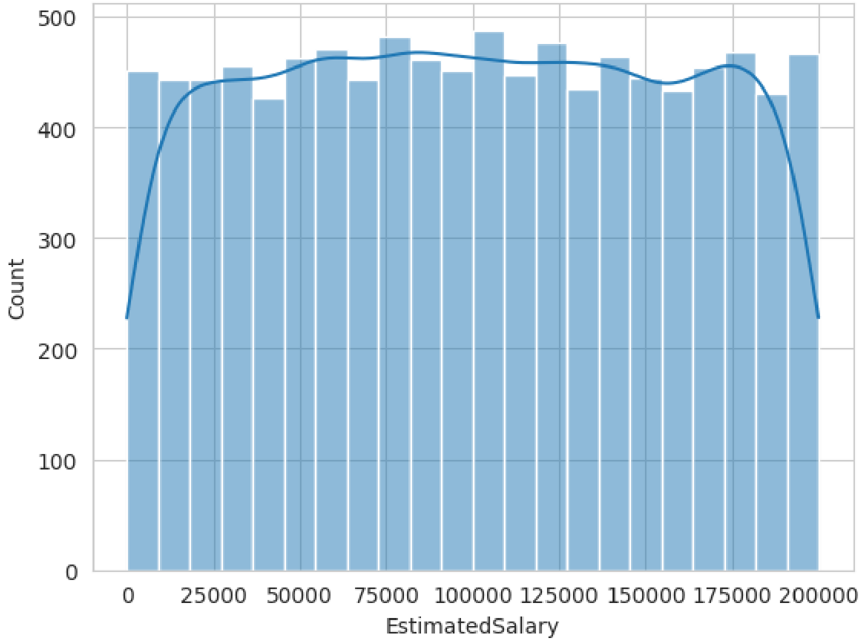


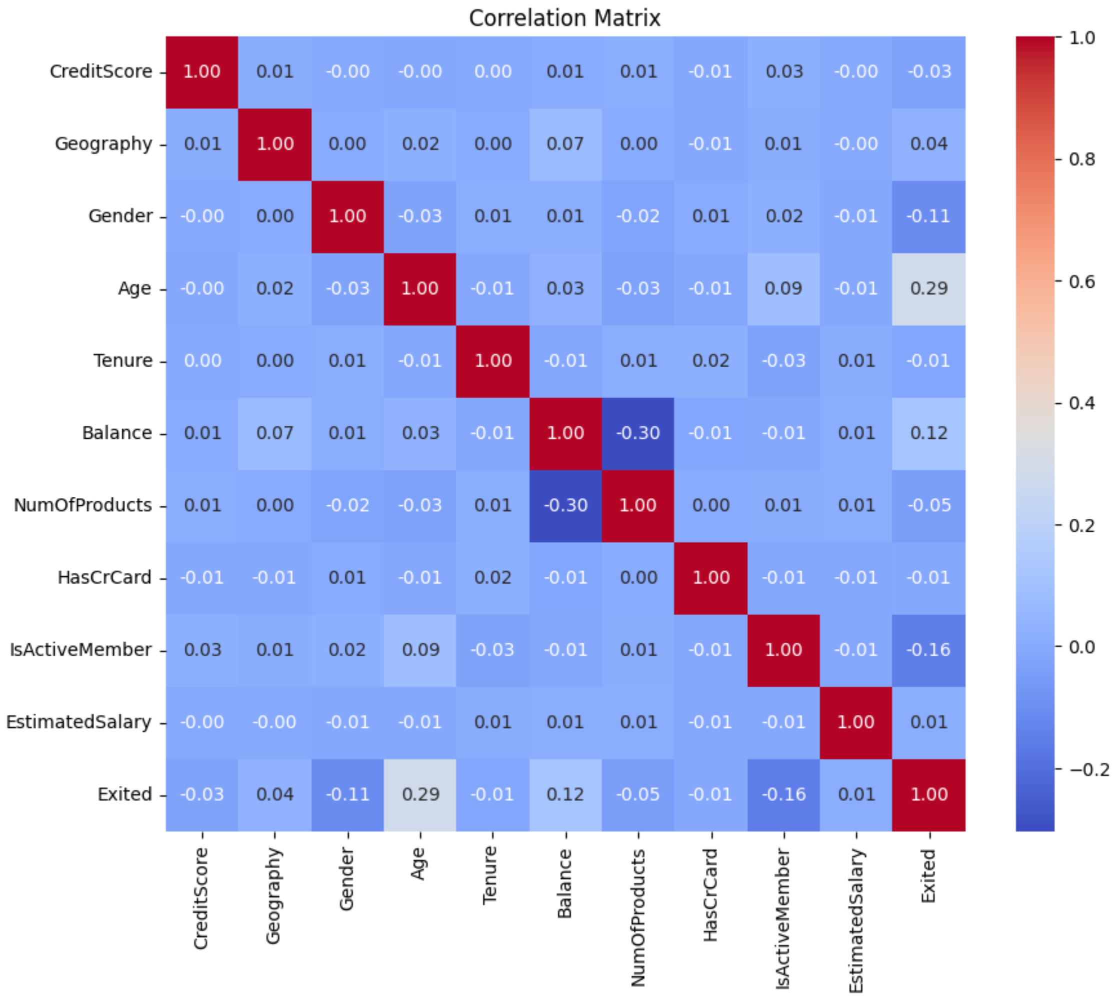
Female

Churn rate : 1139 / 4543

Credit score & estimated salary

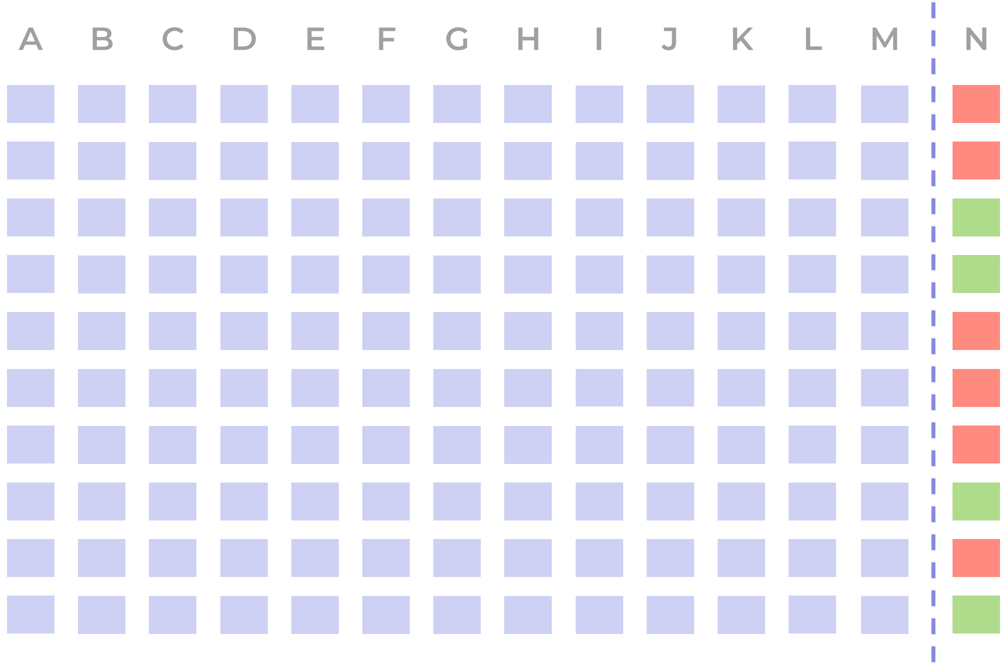





Correlation Matrix
CreditScore
Geography
Gender
Age
Tenure
Balance
NumOfProducts
HasCrCard
IsActiveMember
EstimatedSalary
Exited
1.0
0.8
0.6
0.4
0.2
0.0
−0.2

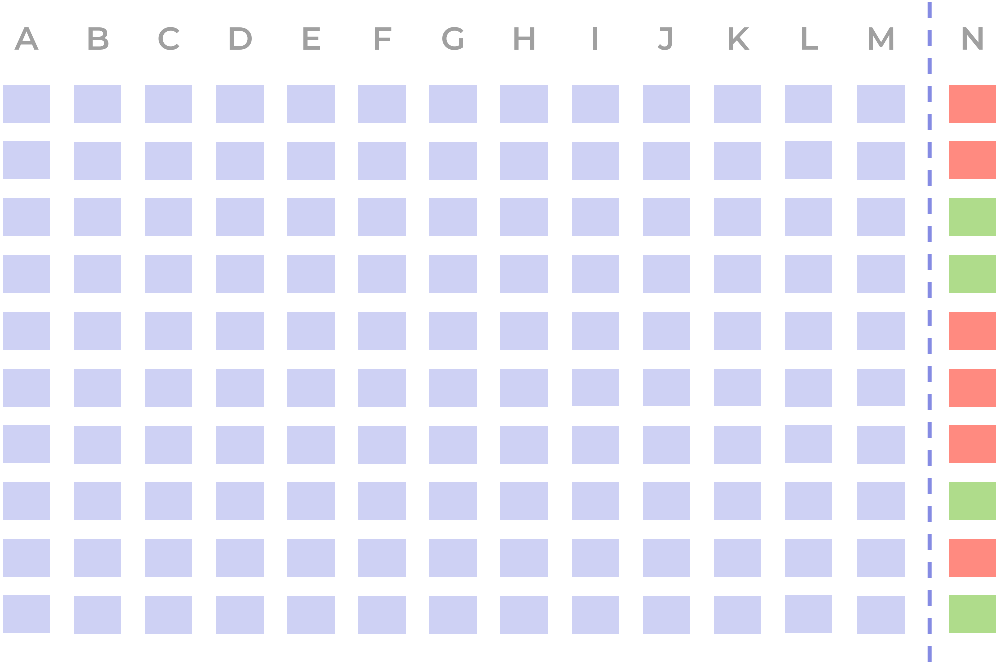
Data preprocessing

Dropping features



A :	row number	H :	tenure
B :	customer id	I :	balance
C :	surname	J :	numOfProducts
D :	credit score	K :	hasCreditCard
E :	geography	L :	isActiveMember
F :	gender	M :	estimatedSalary
G :	age	N :	exited

Dropping features



A : row number

B : customer id

C : surname

D : credit score

E : geography

F : gender

G : age

H : tenure

I : balance

J : numOfProducts

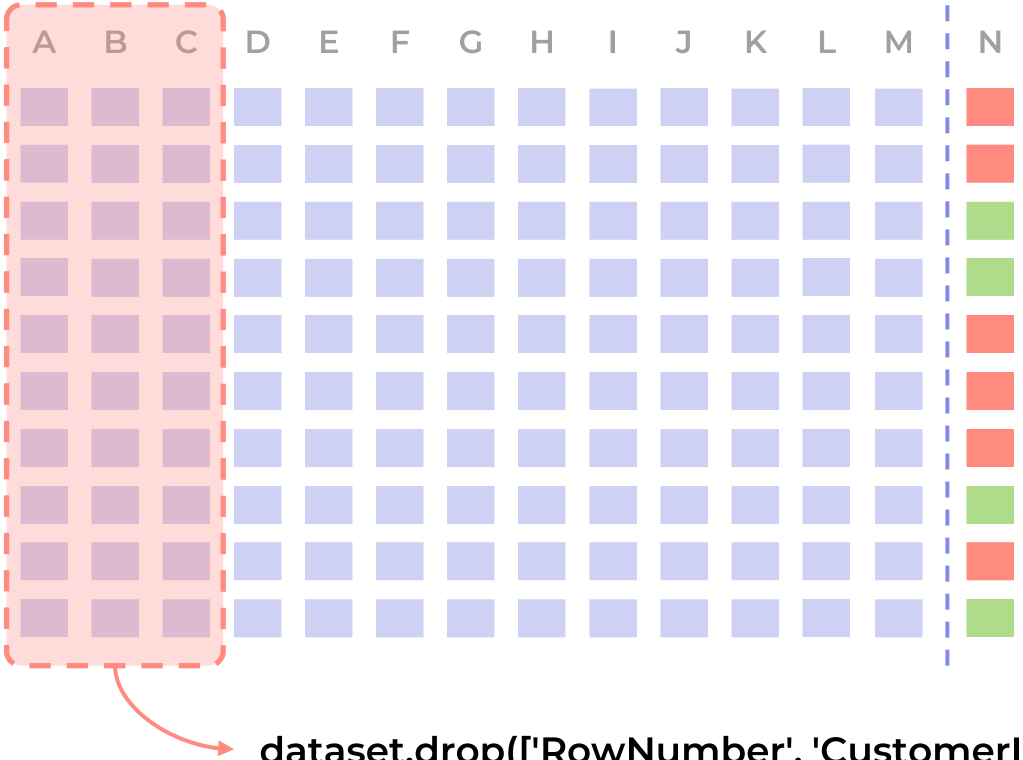
K : hasCreditCard

L : isActiveMember

M : estimatedSalary

N : exited

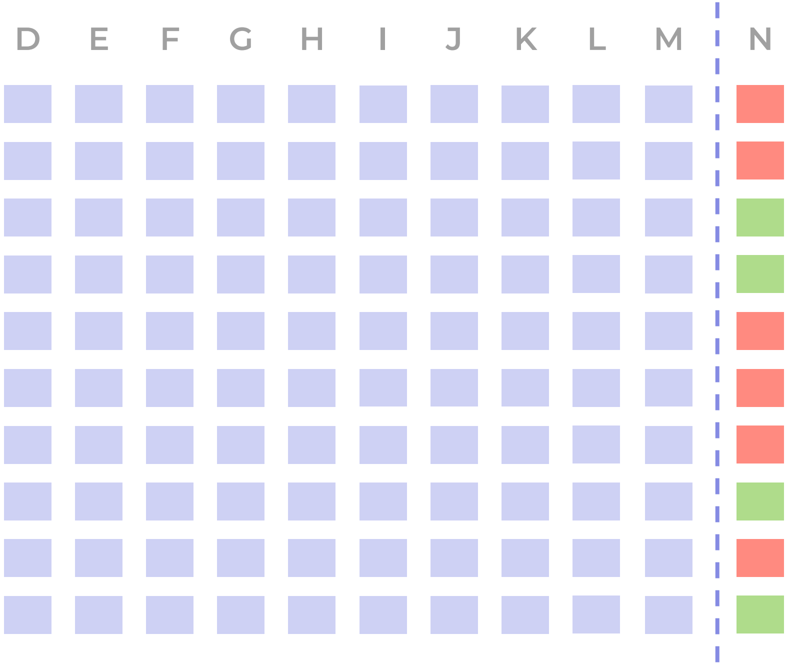
Dropping features



A : row number
B : customer id
C : surname
D : credit score
E : geography
F : gender
G : age
H : tenure
I : balance
J : numOfProducts
K : hasCreditCard
L : isActiveMember
M : estimatedSalary
N : exited

```
dataset.drop(['RowNumber', 'CustomerId', 'Surname’])
```

Dropping features



A : row number

B : customer id

C : surname

D : credit score

E : geography

F : gender

G : age

H : tenure

I : balance

J : numOfProducts

K : hasCreditCard

L : isActiveMember

M : estimatedSalary

N : exited

Converting input types

Gender	Gender
Male	1
Female	0
Female	0
Male	1
Male	0
Female	1

Geography	Geography
Germany	2
France	0
Spain	1
Germany	2
Germany	2
France	0

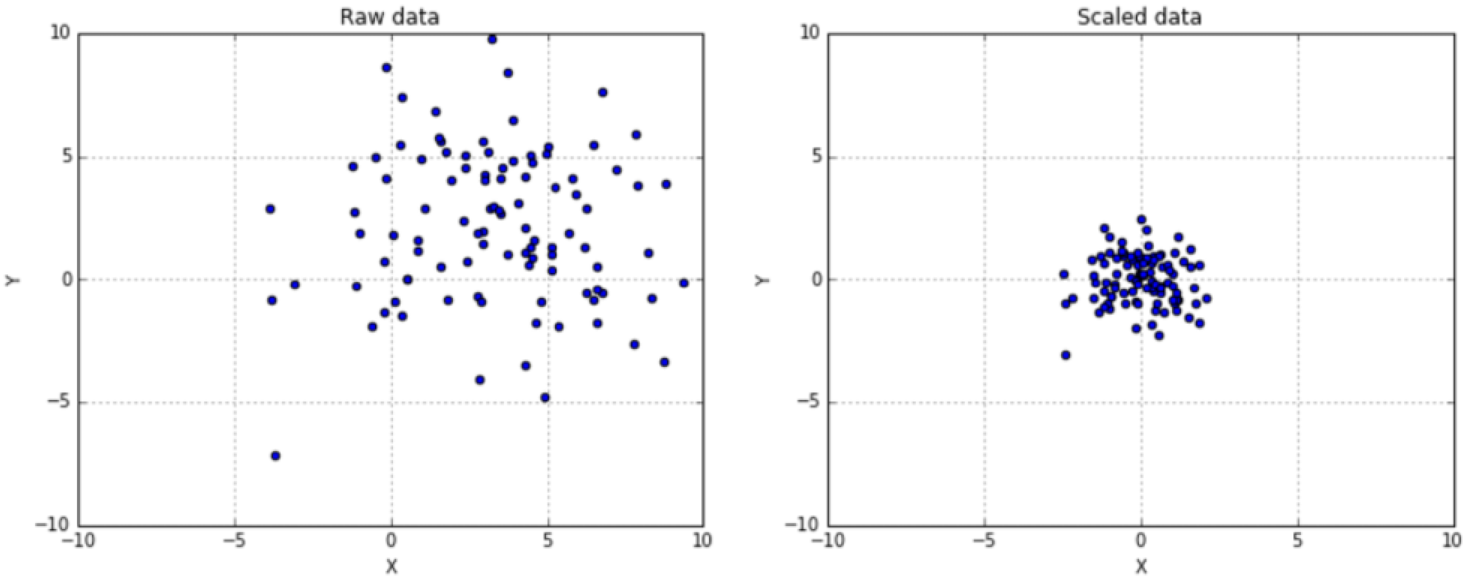
Normalizing salary

```
# Mapping the country to the minimum salary
country_salaries = {'France': 1540 * 12, 'Spain': 1050 * 12, 'Germany': 1580 * 12}

# Remove rows with 'EstimatedSalary' less than 1000
dataset = dataset[dataset['EstimatedSalary'] >= 1000]

# Multiply 'EstimatedSalary' by 12 if it's less than the corresponding country's salary
dataset.loc[dataset['EstimatedSalary'] < dataset['Geography'].map(country_salaries),
'EstimatedSalary'] *= 12
```

Feature scaling



Handle imbalanced data

20%

Initial dataset

Imbalanced - 2037 / 7963

smt = SMOTE(random_state=5)

50%

Final dataset

Balanced - 7963 / 7963

Model training

Results comparison

Classifier	F1-score	Accuracy	Recall	Auc
KNN	85%	85%	85%	92%
Decision Tree	84%	84%	84%	84%
MLP	83%	83%	83%	91%
SVC	80%	81%	81%	89%
Gaussian Naive Bayes	73%	73%	73%	81%

Hyperparameter Tuning

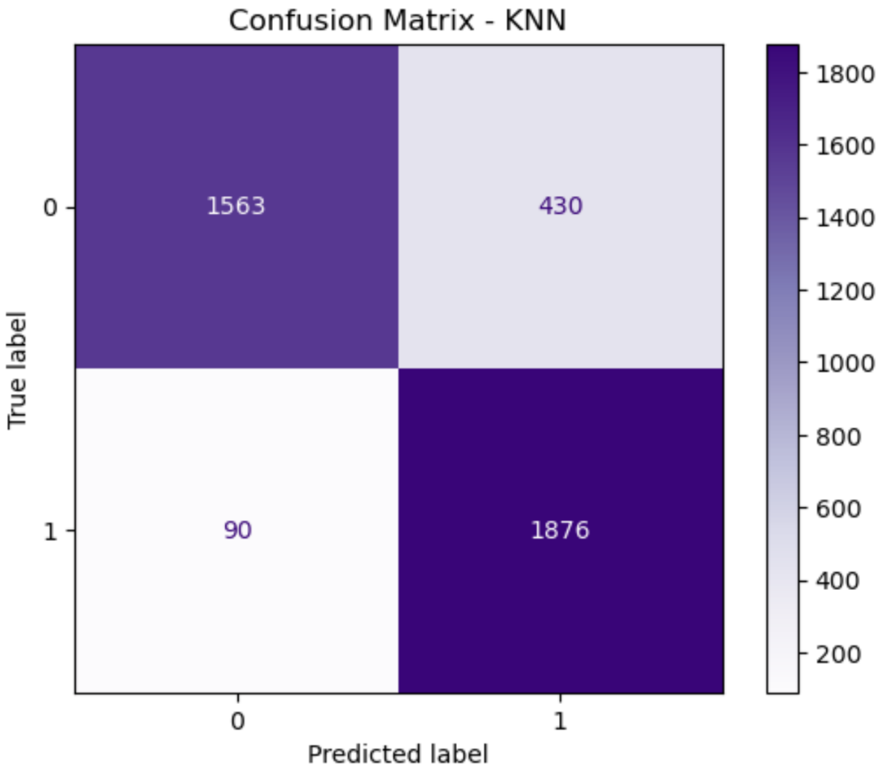
Hyperparameter tuning

- Training and test set sizes
- K-fold cross validation
- Balanced vs imbalanced datasets
- Decision tree criterias
- K-nearest neighbors proximity metric
- SVM kernel function
- Neural networks activation functions and optimizers

Results comparison

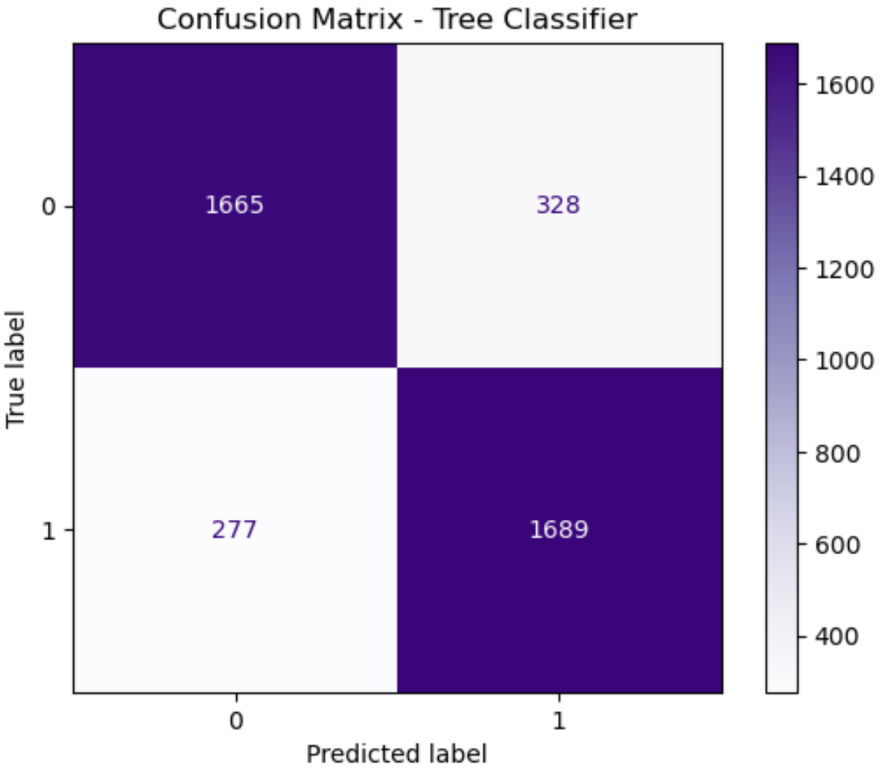
Classifier	F1 Score	Accuracy	Recall	AUC
KNNeighbors	87%	86%	87%	93%
Decision tree	84%	84%	84%	84%
Neural Network	83%	83%	83%	92%
SVC	80%	81%	81%	89%

KNN-Neighbors



	precision	recall	f1-score	support
0	0.95	0.78	0.86	1993
1	0.81	0.95	0.88	1966
accuracy			0.87	3959
macro avg	0.88	0.87	0.87	3959
weighted avg	0.88	0.87	0.87	3959

Decision tree



	precision	recall	f1-score	support
0	0.86	0.83	0.85	1993
1	0.84	0.86	0.85	1966
accuracy			0.85	3959
macro avg	0.85	0.85	0.85	3959
weighted avg	0.85	0.85	0.85	3959

END!