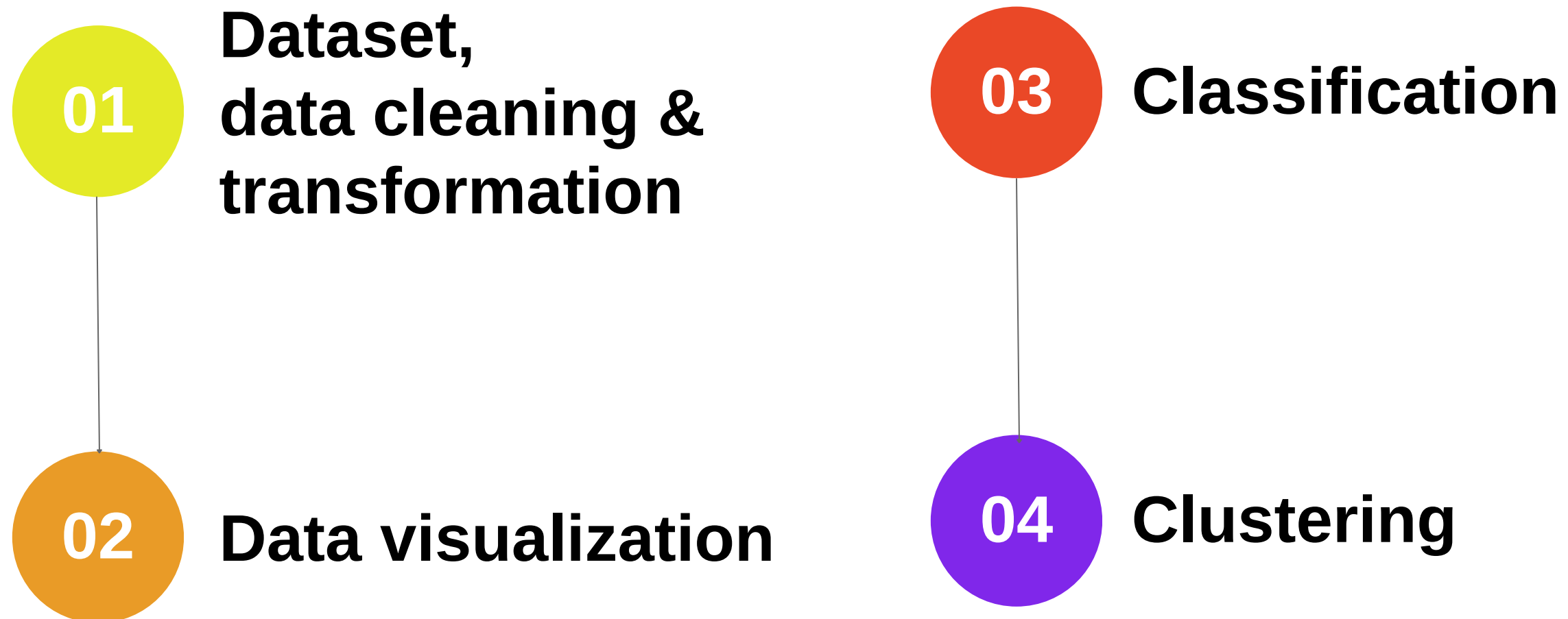


# Project Machine Learning

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# Machine Learning



# Dataset

**Start**

**Diver**

Nom du plongeur

**Nationality**

Nationalité du plongeur

**Gender**

Genre du plongeur (NOC)

**Discipline**

FIM : Immersion libre.  
CNF : Brasse.  
CWT : Poids constant (souvent avec monopalme).  
CWT-B : Poids constant en bi-palmes.

**AP**

Announced performance

**RP**

Realized performance

**Card**

Blanc : Objectif atteint avec protocole respecté.  
Jaune : Profondeur non atteinte mais protocole respecté.  
Rouge : Protocole non respecté.

**Points**

**Remarks**

**Title event**

**Event type**

**Day**

**Line**

Colonne vide

**Official top**

Heure officiel du depart du plongeur

# Data cleaning & transformation

## Explore Diver

```
data.rename(columns={'Diver': 'Name'})
```

## Explore Gender

M	20310
F	11407

```
data['Gender'].map({'M': 'Male', 'F': 'Female'})
```

## Explore Nationality

KOR	3327
FRA	2259
JPN	1932
USA	1740
GBR	1277
...	
MDA	1
KEN	1

## Explore Discipline

CWT	11757
FIM	9473
CNF	5673
CWTB	4814

## Explore AP

Non-Null Count	Dtype
-----	-----
31717 non-null	object

```
data['AP'].str.extract('(\d+)').astype(float)
```

## Explore RP

Non-Null Count	Dtype
-----	-----
31717 non-null	object

```
data['RP'].str.extract('(\d+)').astype(float)
```

## Explore Day

2011-09-15	242
2013-09-15	211
...	
2022-07-25	1

```
pd.to_datetime(df['Day']).dt.month  
pd.to_datetime(df['Day']).dt.year
```

## Explore Card

WHITE	22635
YELLOW	5965
RED	3117

## Explore Points

Non-Null Count	Dtype
-----	-----
31717 non-null	float64

```
data['Points'].apply(lambda x: x if x >= 0 else None)
```

# Data cleaning & transformation

	Name	Nationality	Gender	Discipline	AP	RP	Card	Points	Remarks	Event Type	Month	Year	Season	experience_dive	experience_discipline
0	Deborah Andollo	CUB	Female	CWT	61.0	61.0	WHITE	61.0	OK	Worldrecord attempt	6	1994	Summer	1	1
1	Umberto Pelizzari	ITA	Male	CWT	72.0	72.0	WHITE	72.0	OK	Worldrecord attempt	9	1995	Autumn	1	1
2	Deborah Andollo	CUB	Female	CWT	62.0	62.0	WHITE	62.0	OK	Worldrecord attempt	10	1996	Autumn	2	2
3	Michael Oliva	FRA	Male	CWT	72.0	72.0	WHITE	72.0	OK	Worldrecord attempt	10	1996	Autumn	1	1
4	Alejandro Ravelo	CUB	Male	CWT	73.0	73.0	WHITE	73.0	OK	Worldrecord attempt	8	1997	Summer	1	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
31366	Keenan Alexei Barrameda	PHL	Male	CWT	36.0	36.0	WHITE	36.0	OK	Depth Competition	11	2024	Autumn	6	2
31367	Ramon Paolo Robles	PHL	Male	CWT	33.0	33.0	WHITE	33.0	OK	Depth Competition	11	2024	Autumn	4	1
31368	James Bernard Gabriel	PHL	Male	CNF	25.0	25.0	WHITE	25.0	OK	Depth Competition	11	2024	Autumn	5	1
31369	Franklin Tabora	PHL	Male	CWT	25.0	25.0	WHITE	25.0	OK	Depth Competition	11	2024	Autumn	4	2

+ **experience\_dive**

```
data.groupby('Name').cumcount() + 1
```

+ **experience\_discipline**

```
data.groupby(['Name', 'Discipline']).cumcount() + 1
```

+ **Season**

```
if month in [12, 1, 2]:
    return 'Winter'
elif month in [3, 4, 5]:
    return 'Spring'
elif month in [6, 7, 8]:
    return 'Summer'
else:
    return 'Autumn'
```

# Data cleaning & transformation

```
data.drop_duplicates(inplace=True)
```

```
data.drop(["Start", "Line", "Official Top", "Title Event"], axis=1)
```

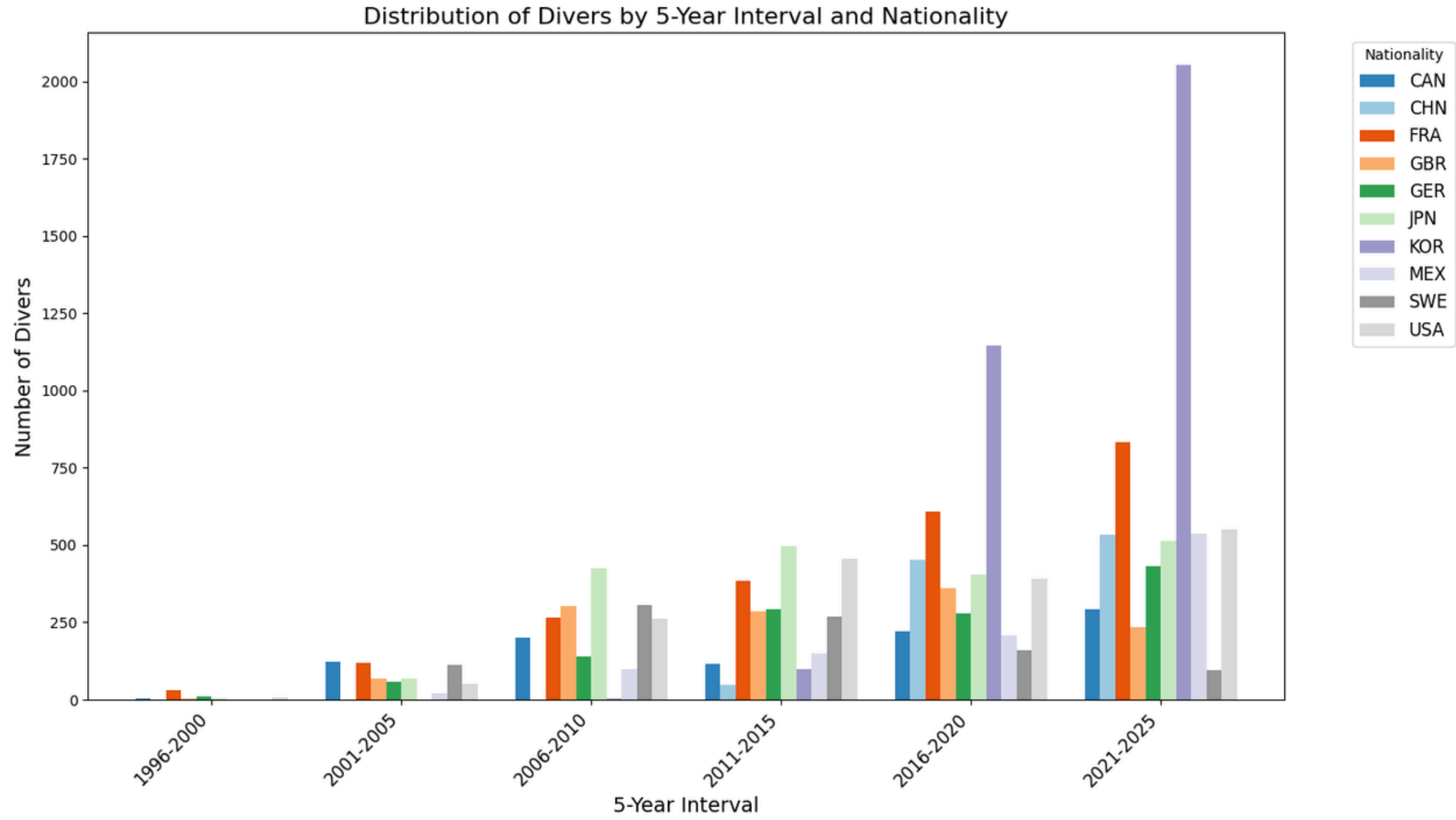
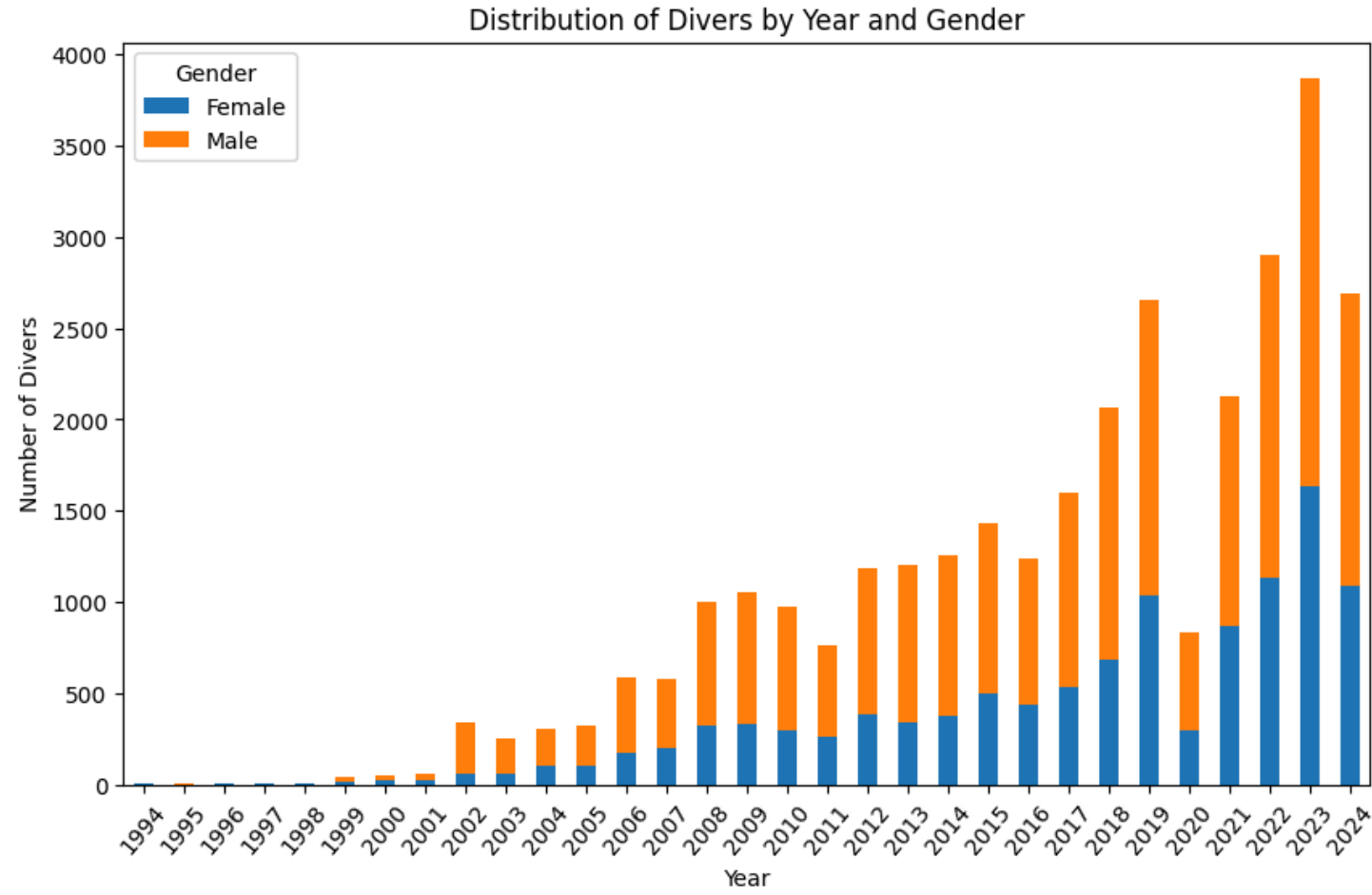
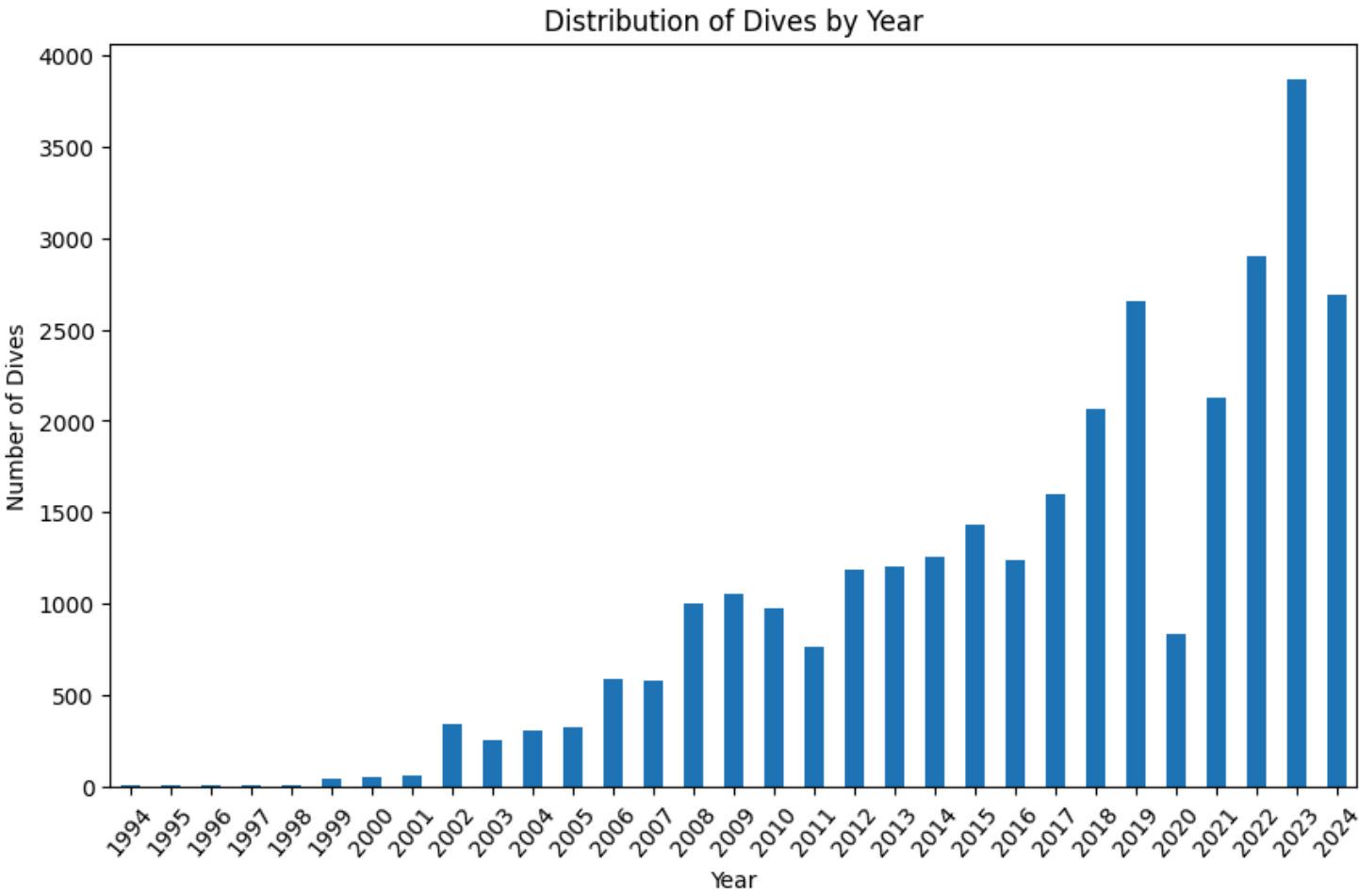
```
data.drop(columns=['Unnamed: 0'], errors='ignore', axis=1)
```

```
data.drop(['Day'], axis=1)
```

```
data.to_csv('Dataset.csv')
```

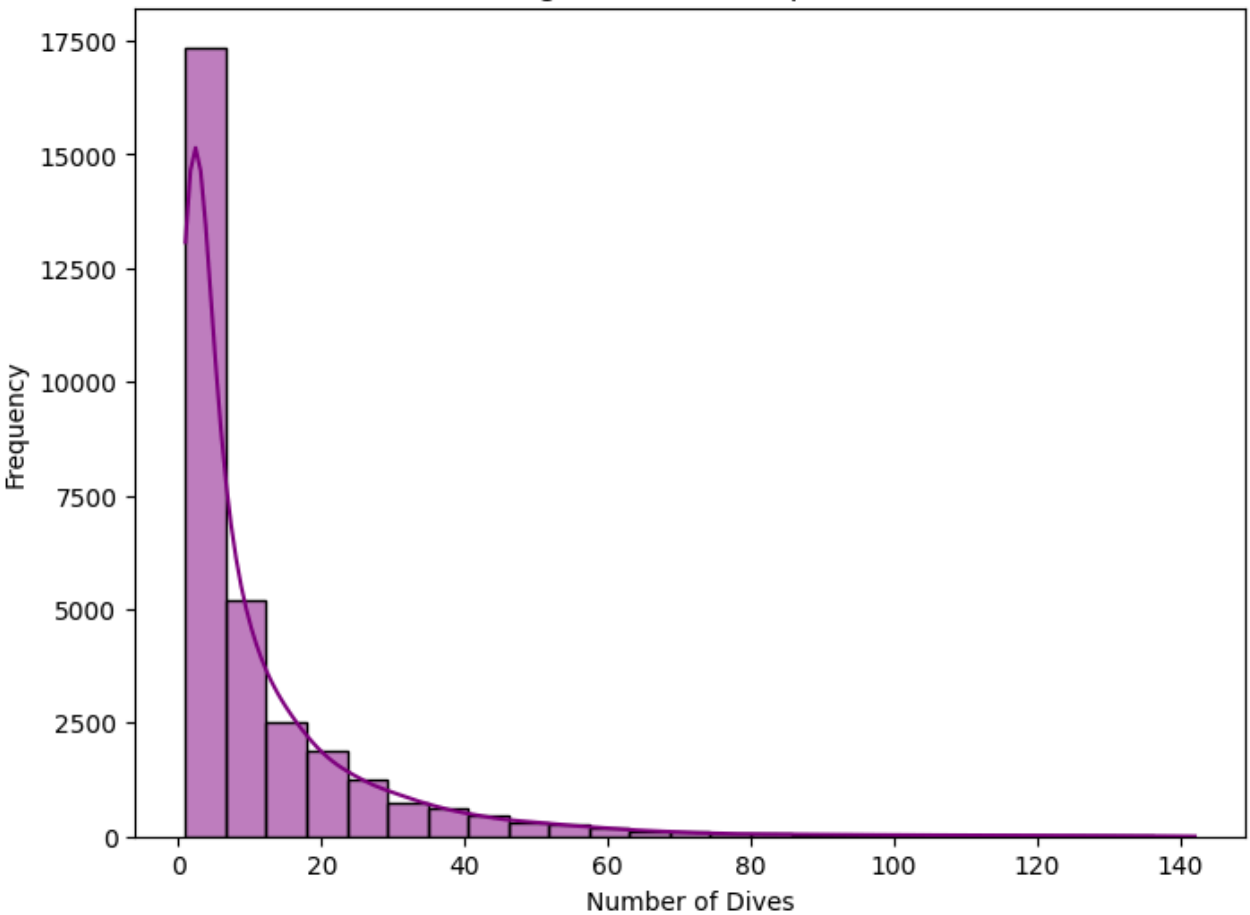


# Data visualization

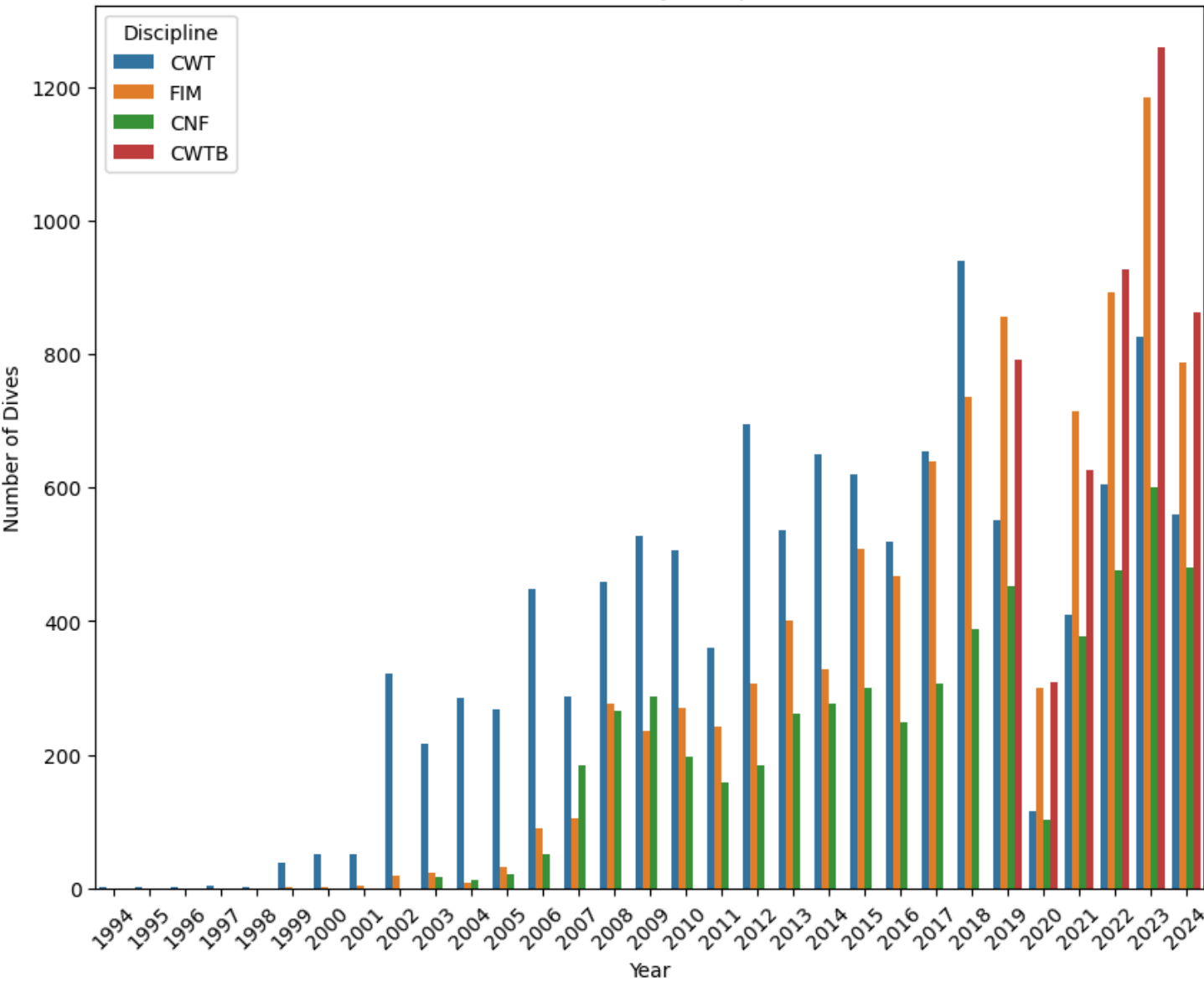


# Data visualization

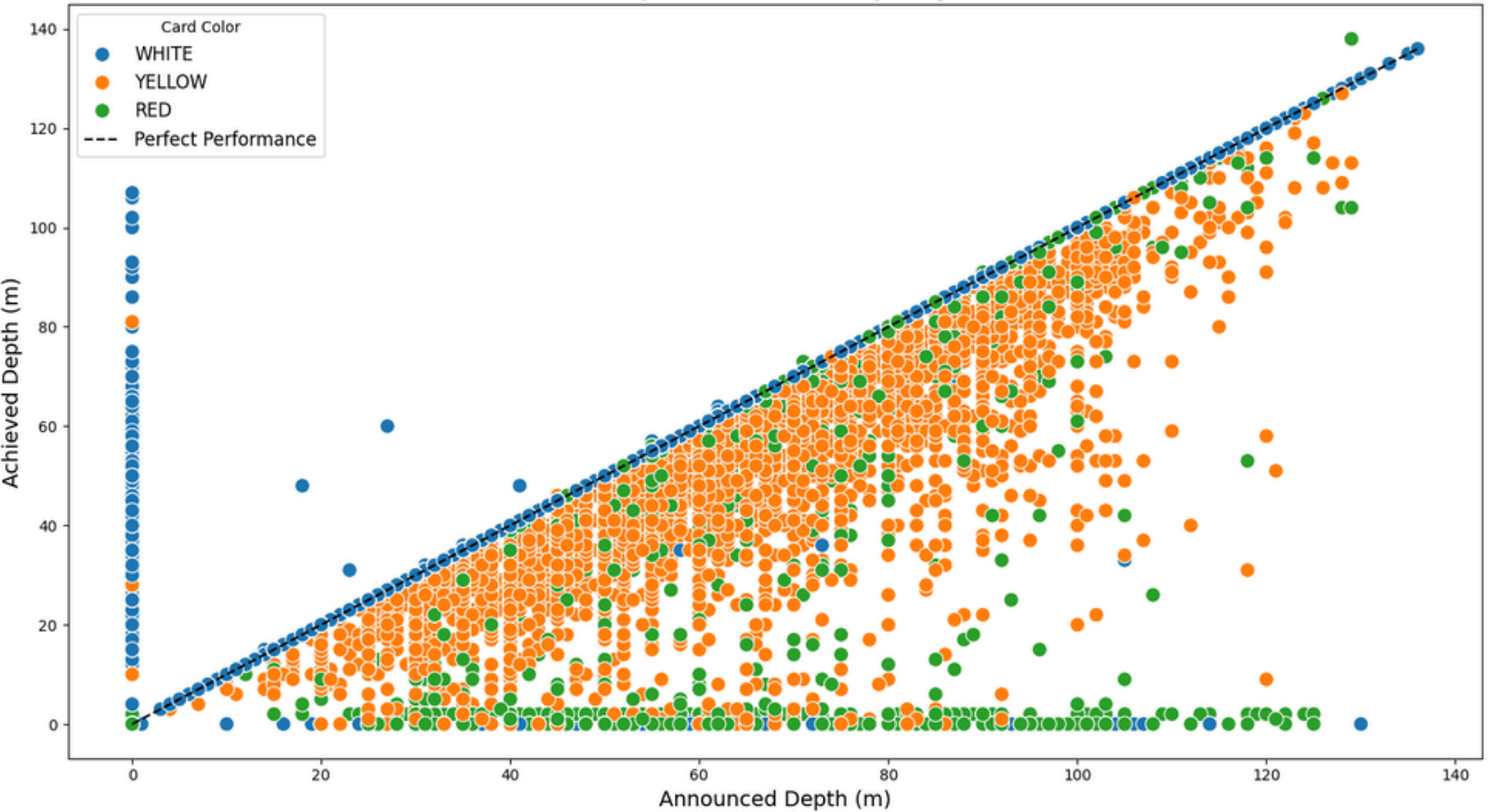
Histogram of Diver Experience



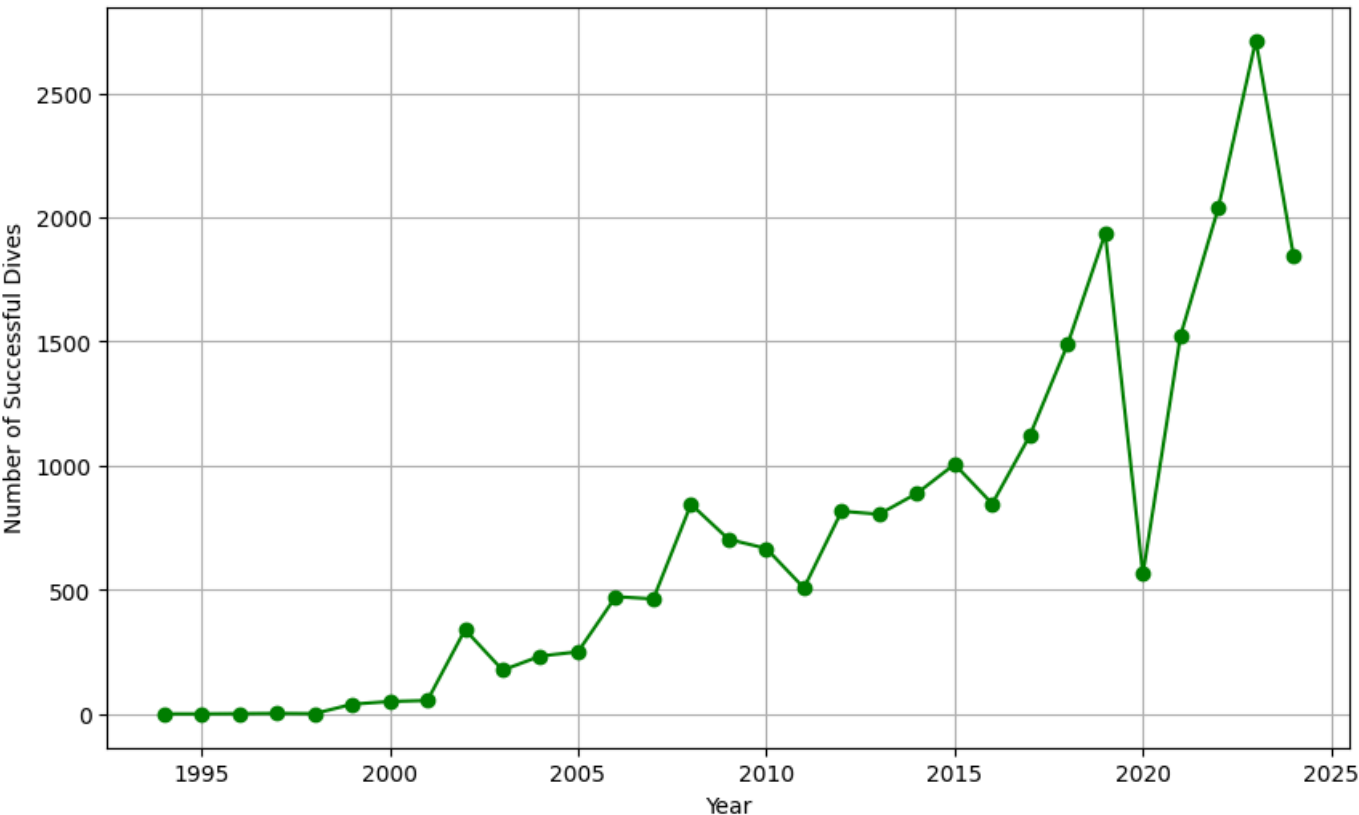
Distribution of Cards by Discipline and Year



Announced Depth vs Achieved Depth by Card Color

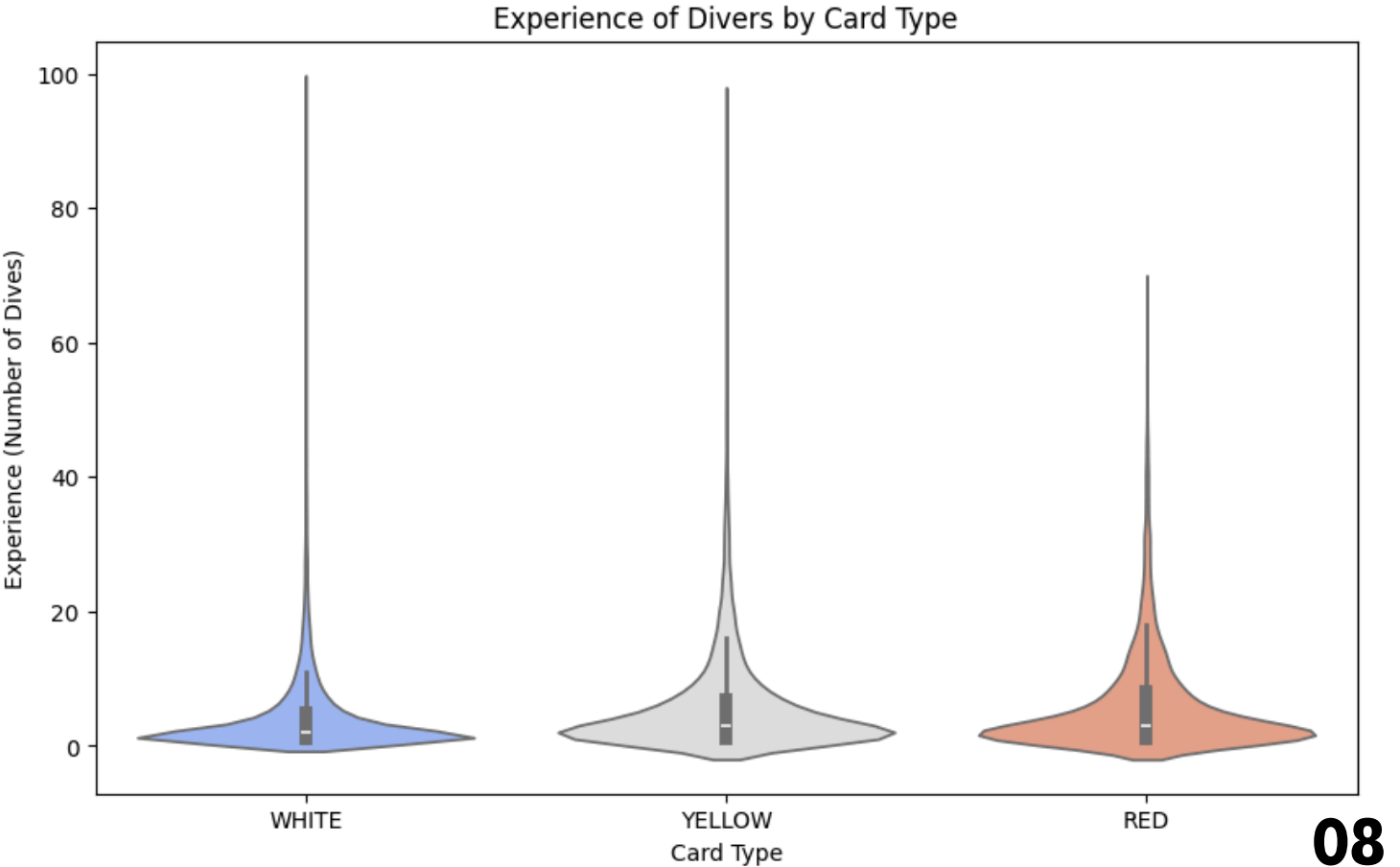
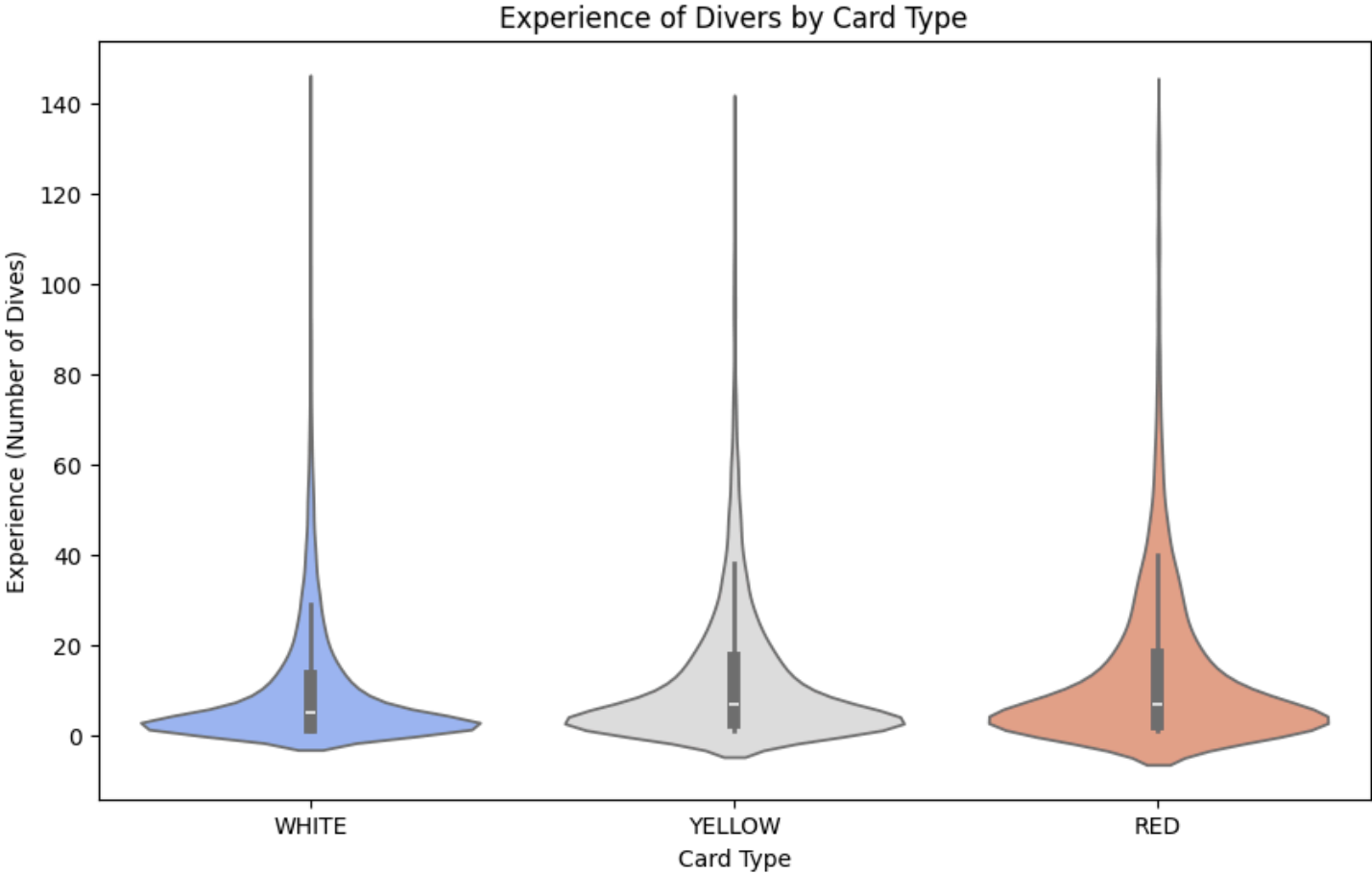
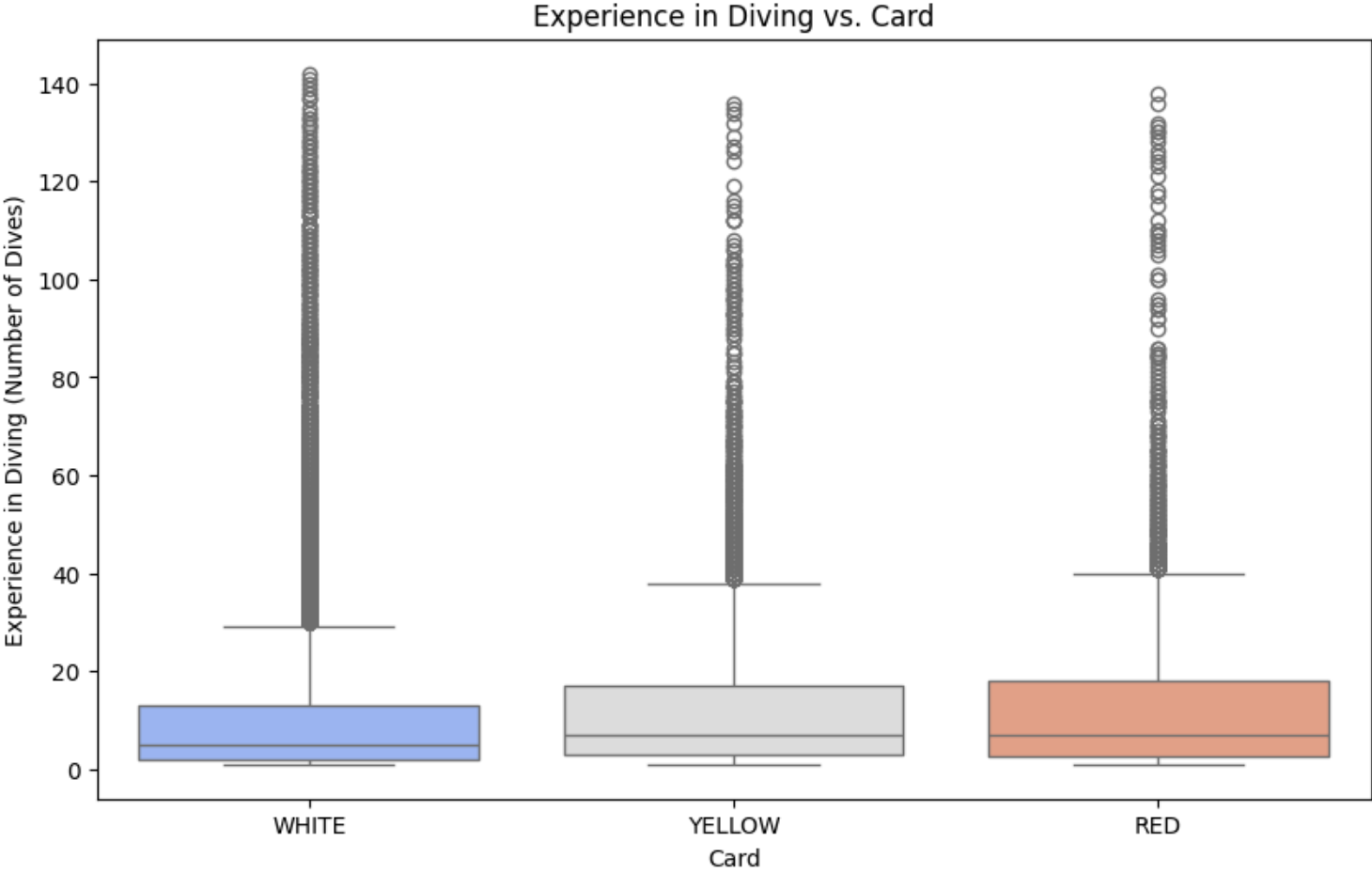
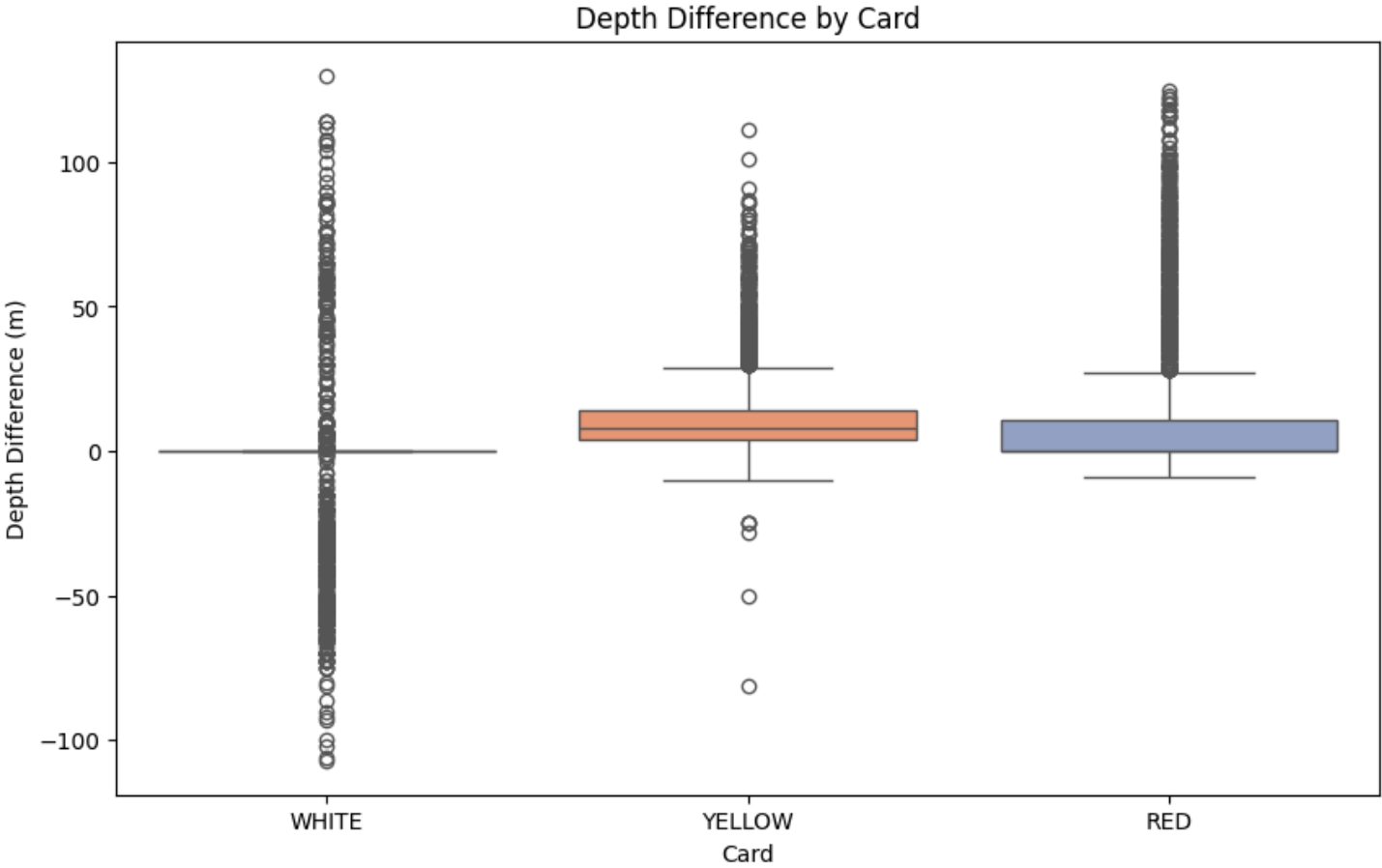


Number of Successful Dives (White Card) Over Time





# Data visualization



# Classification

**Features:** AP, RP, experience\_dive, experience\_discipline, Month, Year

**Target:** Card

**DATA**

**70%**

**30%**

**Train**

**Test**

**SVM**

**Training**

**Predictions**

**Why SVM?**

Classification Report:

	precision	recall	f1-score	support
RED	0.00	0.00	0.00	953
WHITE	0.87	0.99	0.93	6692
YELLOW	0.80	0.81	0.80	1767
accuracy			0.86	9412
macro avg	0.56	0.60	0.58	9412
weighted avg	0.77	0.86	0.81	9412

# Classification

Features: AP, RP, experience\_dive, experience\_discipline, Month, Year

Target: Card

WHITE

22635

YELLOW

5965

RED

3117

```
graph TD; DATA[DATA] -- 70% --> Train[Train]; DATA -- 15% --> Validation[Validation]; DATA -- 15% --> Test[Test]; DATA -- "Sample 5000 random rows" --> Sample[Sample 5000 random rows];
```

SVM (Linear, Poly, RBF)

Training

Predictions

C = 1.0

RED: 2.2  
WHITE: 1.0  
YELLOW: 2.0

Linear

Poly

Rbf

Test Classification Report:				
	precision	recall	f1-score	support
RED	0.33	0.46	0.39	460
WHITE	0.71	0.50	0.58	750
YELLOW	0.84	0.88	0.86	885
accuracy			0.65	2095
macro avg	0.63	0.61	0.61	2095
weighted avg	0.68	0.65	0.66	2095

Test Classification Report:				
	precision	recall	f1-score	support
RED	0.39	0.42	0.40	460
WHITE	0.77	0.17	0.28	750
YELLOW	0.56	0.92	0.70	885
accuracy			0.54	2095
macro avg	0.58	0.50	0.46	2095
weighted avg	0.60	0.54	0.48	2095

Test Classification Report:				
	precision	recall	f1-score	support
RED	0.41	0.61	0.49	460
WHITE	0.69	0.54	0.61	750
YELLOW	0.87	0.81	0.84	885
accuracy			0.67	2095
macro avg	0.66	0.66	0.65	2095
weighted avg	0.71	0.67	0.68	2095

10

# Classification

**Features:** AP, RP, experience\_dive, experience\_discipline, Month, Year

**Target:** Card

**WHITE**

22635

**YELLOW**

5965

**RED**

3117

**DATA**

Sample 5000  
random rows

70%

**Train**

15%

**Validation**

15%

**Test**

**Random Forest Classifier**

**Training**

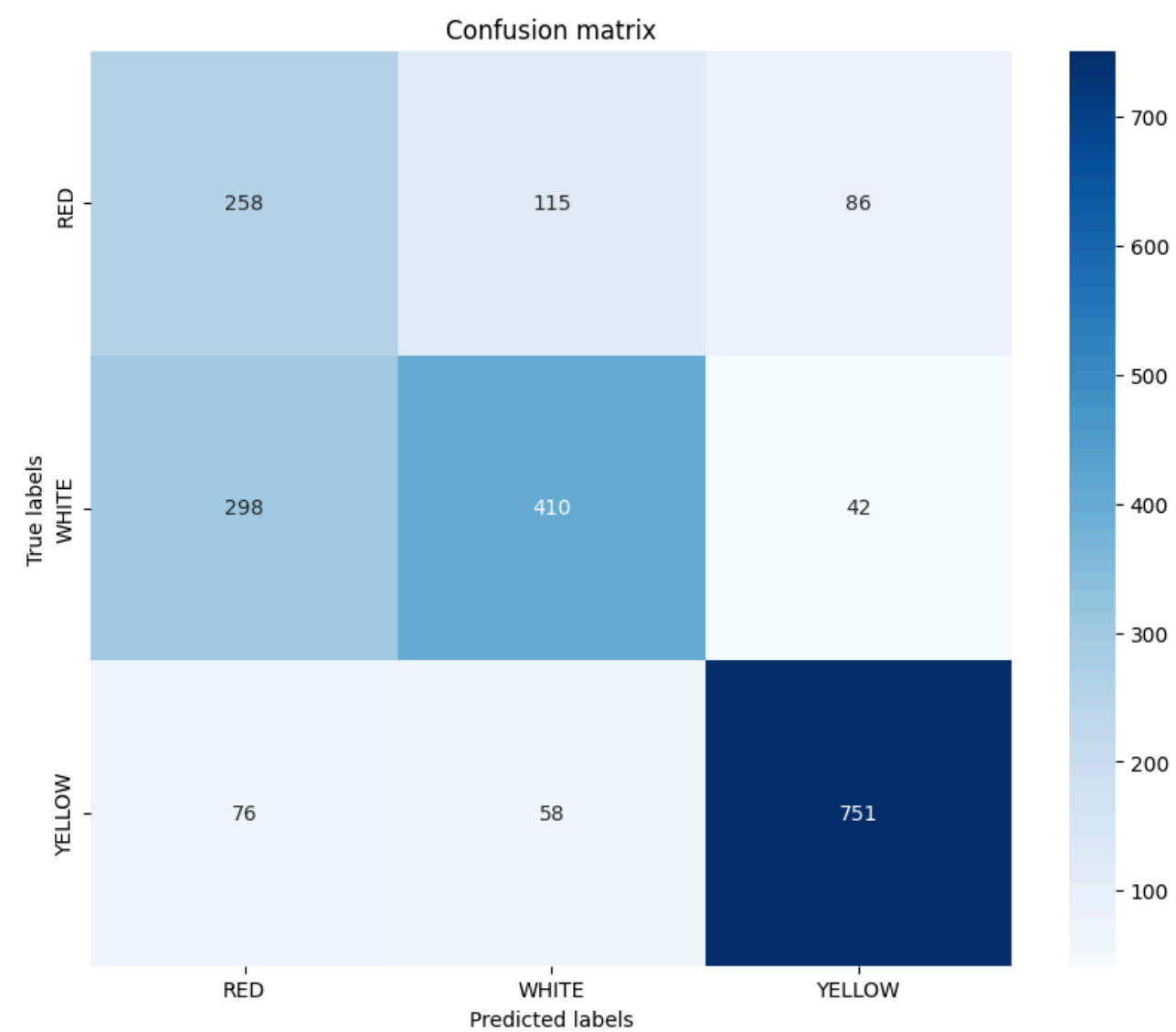
**Predictions**

**Balanced**

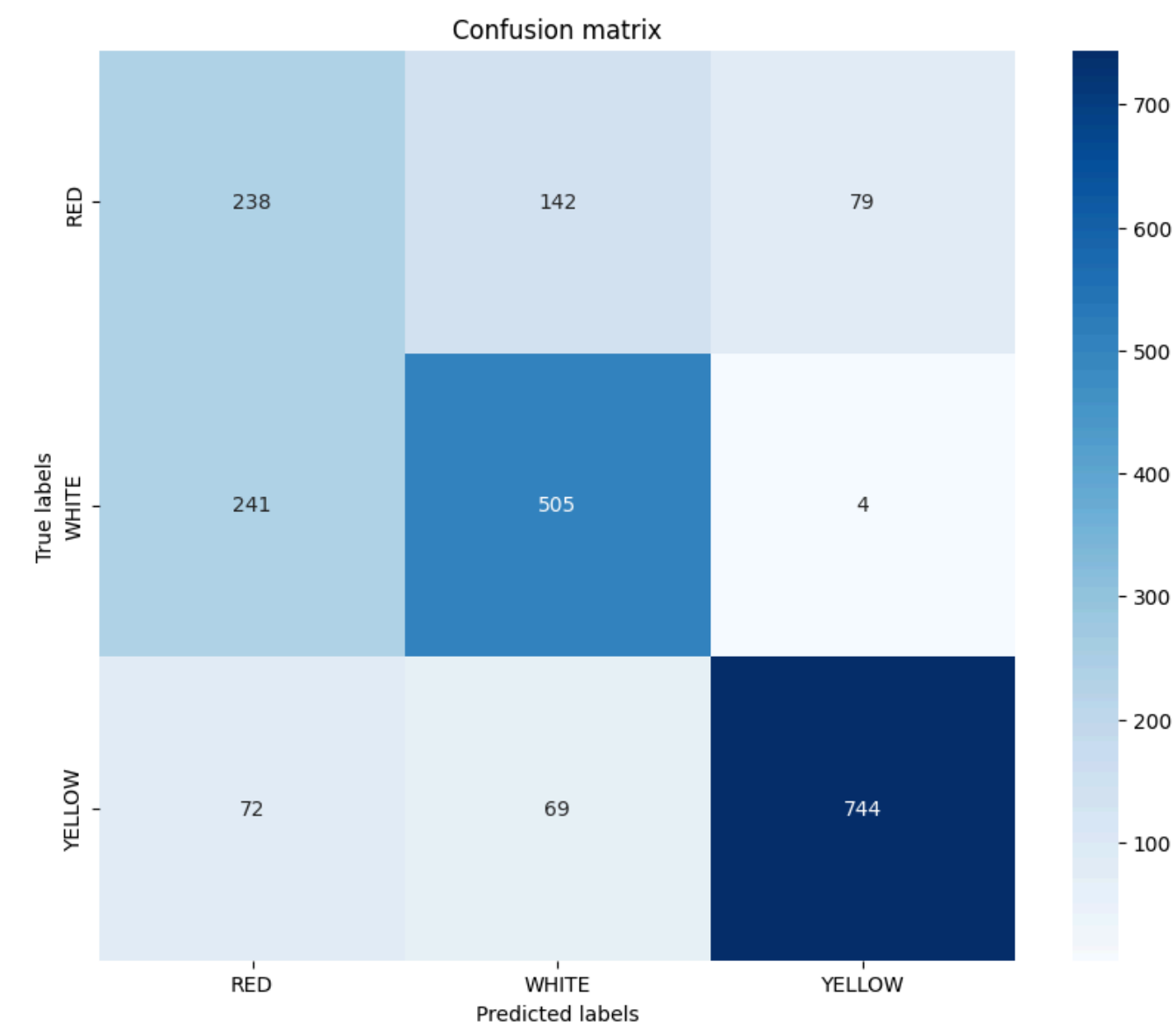
	precision	recall	f1-score	support
RED	0.52	0.44	0.48	459
WHITE	0.67	0.78	0.72	750
YELLOW	0.87	0.83	0.85	885
accuracy			0.72	2094
macro avg	0.69	0.68	0.68	2094
weighted avg	0.72	0.72	0.72	2094

# Classification

With SVM (rbf kernel)



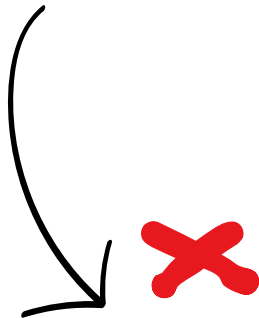
With Random Forest Classifier



	Model	Accuracy	Precision	Recall
0	Random Forest	0.710124	0.678962	0.677510
1	SVM (Linear)	0.655683	0.625709	0.614291
2	SVM (RBF)	0.677650	0.655289	0.652449
3	SVM (Polynomial)	0.543935	0.590666	0.506769

# Clustering

on procède à un cleaning avant de commencer



et on change les NaN par des 0

```
# 1. Remplacer les NaN par 0
data.fillna(0, inplace=True)
```

```
print(data.isna().sum()) #plus de NaN car tout a été bien remplacé par 0
✓ 0.0s
```

Unnamed: 0 0  
Name 0  
AP 0  
RP 0  
Card 0  
..  
Nationality\_ZWE 0  
Gender\_Male 0  
Discipline\_CWT 0  
Discipline\_CWTB 0  
Discipline\_FIM 0  
Length: 131, dtype: int64

	Unnamed: 0	Name	Nationality	Gender	Discipline	AP	RP	Card	Points	Remarks	Event Type	Month	Year	Season	experience_dive	experience_discipline
0	0	Deborah Andollo	CUB	Female	CWT	61.0	61.0	WHITE	61.0	OK	Worldrecord attempt	6	1994	Summer	1	1
1	1	Umberto Pelizzari	ITA	Male	CWT	72.0	72.0	WHITE	72.0	OK	Worldrecord attempt	9	1995	Autumn	1	1
2	2	Deborah Andollo	CUB	Female	CWT	62.0	62.0	WHITE	62.0	OK	Worldrecord attempt	10	1996	Autumn	2	2
3	3	Michael Oliva	FRA	Male	CWT	72.0	72.0	WHITE	72.0	OK	Worldrecord attempt	10	1996	Autumn	1	1
4	4	Alejandro Ravelo	CUB	Male	CWT	73.0	73.0	WHITE	73.0	OK	Worldrecord attempt	8	1997	Summer	1	1

# Clustering

1. On change les données “catégoriques” en données “numériques”

TRANSFORMATION DES DONNEES CATEGORIE EN NUMERIQUE (car le clustering ne fonctionne pas sur des données numériques)

```
from sklearn.preprocessing import LabelEncoder

# Colonnes à encoder
columns_to_encode_red = ['Discipline', 'Nationality', 'Gender'] # 'Discipline' existe dans red_dives
columns_to_encode_white = ['Nationality', 'Gender'] # 'Discipline' n'est pas dans white_dives

encoder = LabelEncoder()

numeric_data = encoder.fit_transform(data["Card"])
print(numeric_data)
```

✓ 1.4s

[1 1 1 ... 1 1 1]

2. On normalise les données

NORMALISATION DES DONNEES POUR QUE TOUTES LES COLONNES SOIENT COMPARABLES EN TERME DE DISTANCE EUCLIDIENNE

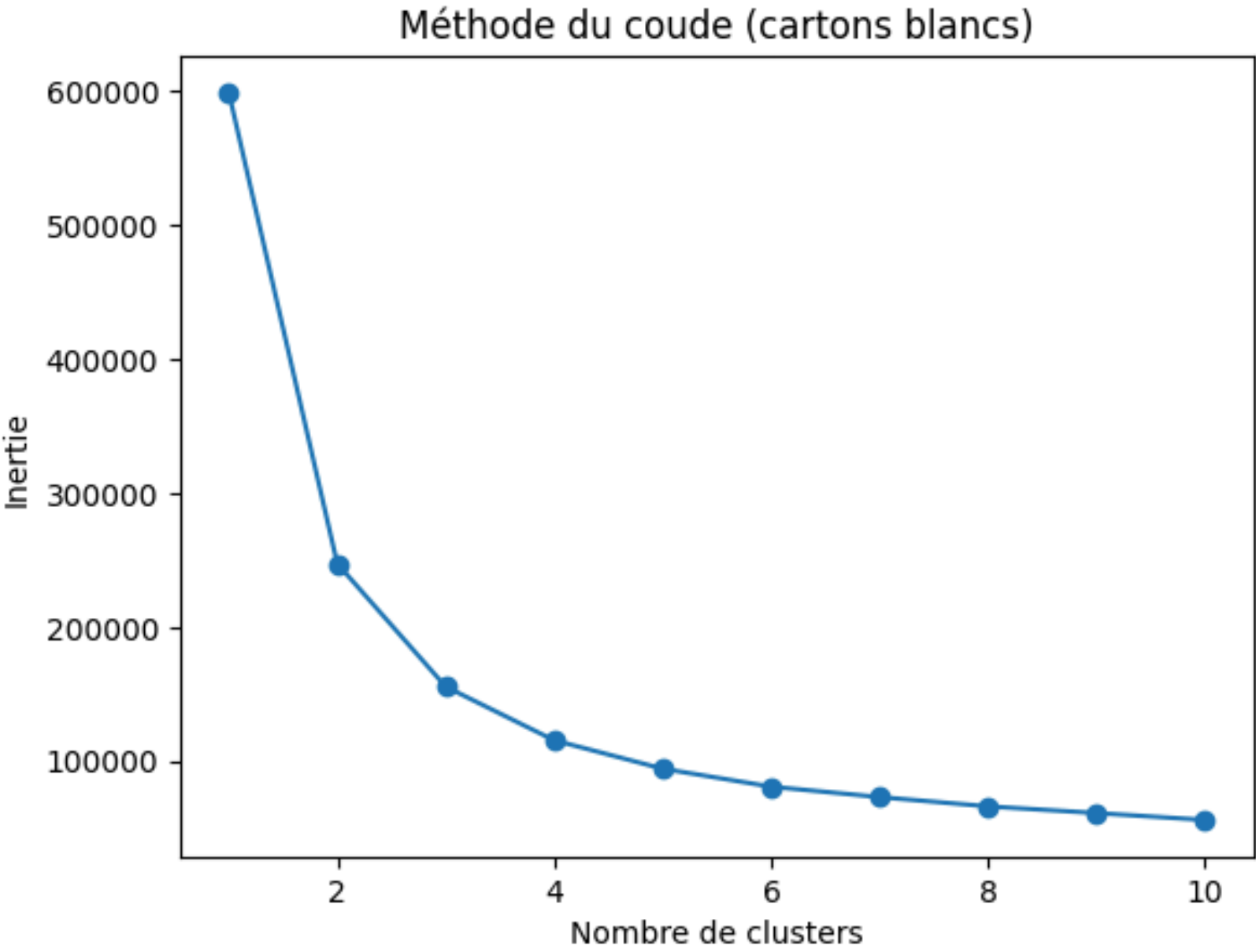
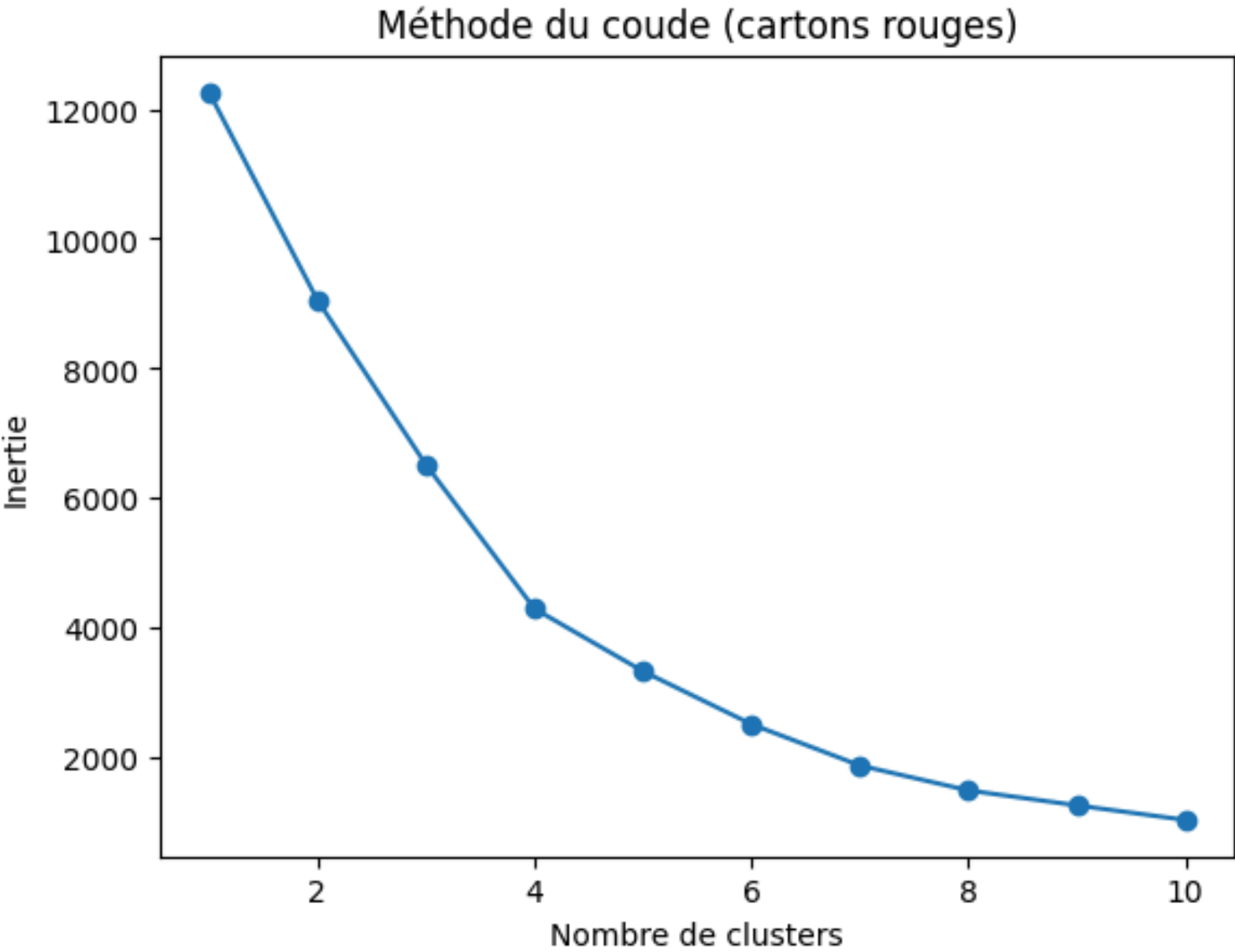
```
from sklearn.preprocessing import StandardScaler

# Liste des colonnes à normaliser
features_to_normalize = ['Name', 'Nationality', 'Gender', 'Discipline', 'AP', 'RP',
                          'Card', 'Points', 'Remarks', 'Event Type', 'Month', 'Year', 'Season',
                          'experience_dive', 'experience_discipline']

# Normalisation
scaler = StandardScaler()
```

✓ 0.0s

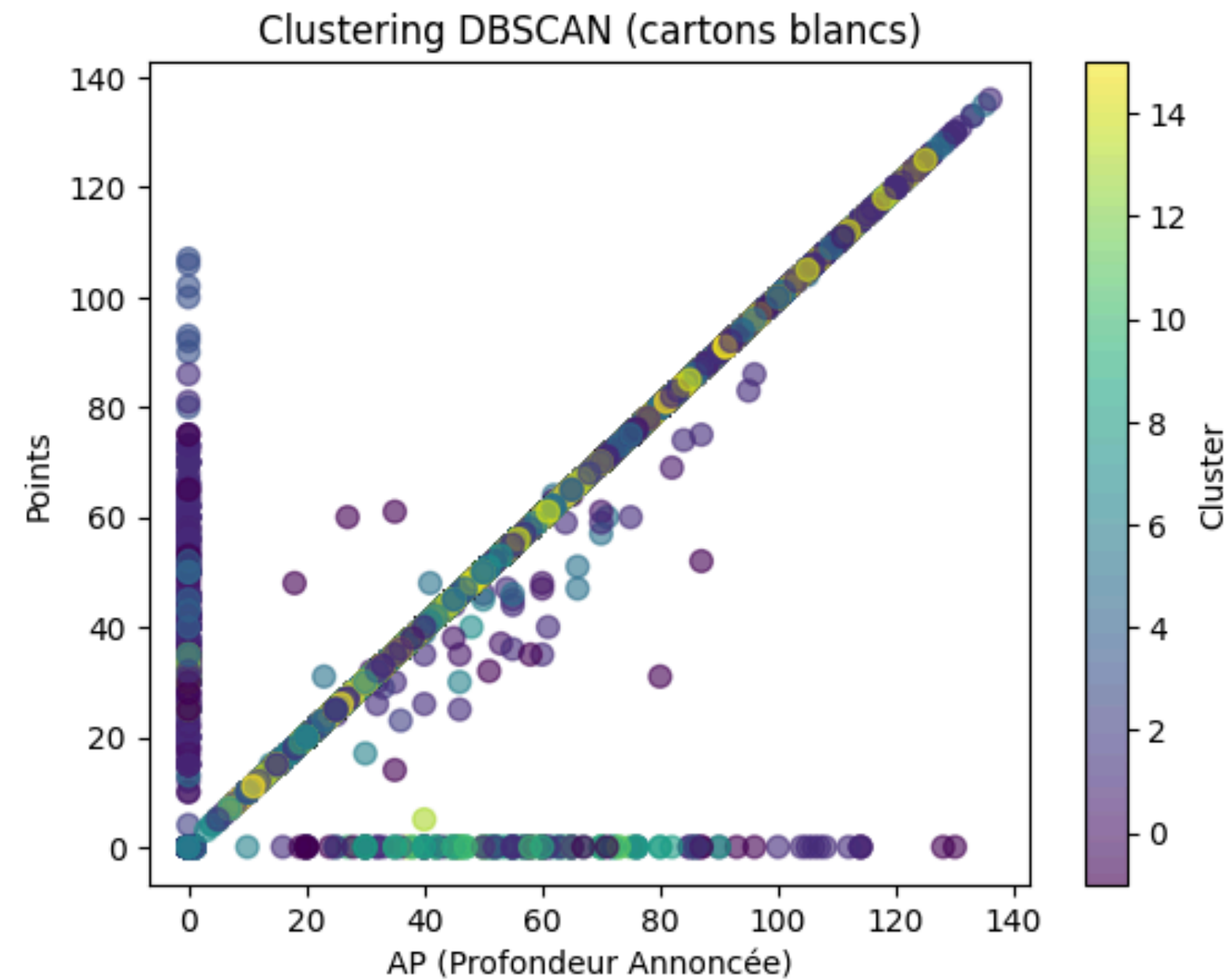
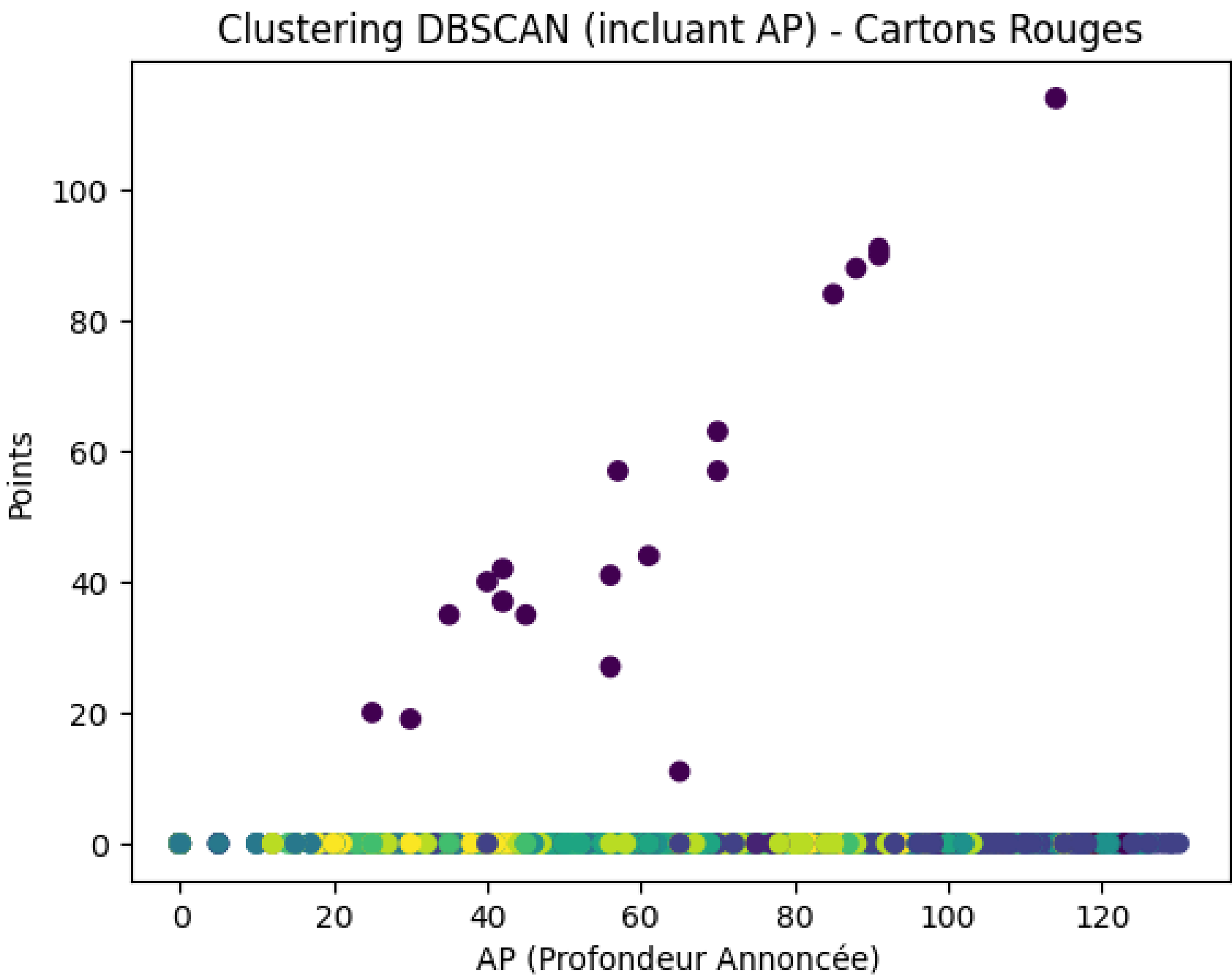
# Clustering (visualisation)





# Clustering (visualisation)

inclure AP était plus concluant  
quand on a exclus RP



# Sources

pandas documentation – pandas 2.2.3 documentation

Matplotlib – Visualization with Python

seaborn: statistical data visualization – seaborn 0.13.2 documentation

scikit-learn: machine learning in Python – scikit-learn 1.5.2 documentation

SVC – scikit-learn 1.5.2 documentation

train\_test\_split – scikit-learn 1.5.2 documentation

confusion\_matrix – scikit-learn 1.5.2 documentation

RandomForestClassifier – scikit-learn 1.5.2 documentation

StandardScaler – scikit-learn 1.5.2 documentation

LabelEncoder – scikit-learn 1.5.2 documentation