

Importing Libraries and Dataset

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, classification_report
from sklearn.ensemble import GradientBoostingClassifier,
RandomForestClassifier, AdaBoostClassifier
from sklearn.svm import SVC, LinearSVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression, SGDClassifier
from sklearn.neural_network import MLPClassifier
from xgboost import XGBClassifier
```

```
import warnings
warnings.filterwarnings("ignore")
```

```
df = pd.read_csv("Data\pokemon.csv")
```

```
df.head()
```

	abilities	against_bug	against_dark
against_dragon \			
0	['Overgrow', 'Chlorophyll']	1.0	1.0
1.0			
1	['Overgrow', 'Chlorophyll']	1.0	1.0
1.0			
2	['Overgrow', 'Chlorophyll']	1.0	1.0
1.0			
3	['Blaze', 'Solar Power']	0.5	1.0
1.0			
4	['Blaze', 'Solar Power']	0.5	1.0
1.0			

	against_electric	against_fairy	against_fight	against_fire \
0	0.5	0.5	0.5	2.0
1	0.5	0.5	0.5	2.0
2	0.5	0.5	0.5	2.0
3	1.0	0.5	1.0	0.5
4	1.0	0.5	1.0	0.5

	against_flying	against_ghost	...	percentage_male	pokedex_number
\					

0	2.0	1.0	...	88.1	1
1	2.0	1.0	...	88.1	2
2	2.0	1.0	...	88.1	3
3	1.0	1.0	...	88.1	4
4	1.0	1.0	...	88.1	5

	sp_attack	sp_defense	speed	type1	type2	weight_kg	generation
0	65	65	45	grass	poison	6.9	1
1	80	80	60	grass	poison	13.0	1
2	122	120	80	grass	poison	100.0	1
3	60	50	65	fire	NaN	8.5	1
4	80	65	80	fire	NaN	19.0	1

	is_legendary
0	0
1	0
2	0
3	0
4	0

[5 rows x 41 columns]

Descriptive Statistics

```
df.shape      # 801 pokemons, 41 attributes
```

```
(801, 41)
```

```
df.columns.values  # columns
```

```
array(['abilities', 'against_bug', 'against_dark', 'against_dragon',
       'against_electric', 'against_fairy', 'against_fight',
       'against_fire', 'against_flying', 'against_ghost',
       'against_grass',
       'against_ground', 'against_ice', 'against_normal',
       'against_poison', 'against_psychic', 'against_rock',
       'against_steel', 'against_water', 'attack', 'base_egg_steps',
       'base_happiness', 'base_total', 'capture_rate',
```

```
'classification',
      'defense', 'experience_growth', 'height_m', 'hp',
'japanese_name',
      'name', 'percentage_male', 'pokedex_number', 'sp_attack',
      'sp_defense', 'speed', 'type1', 'type2', 'weight_kg',
'generation',
      'is_legendary'], dtype=object)
```

```
df.sample(5).T
```

	24	680 \
abilities	['Static', 'Lightningrod']	['Stance Change']
against_bug	1.0	0.25
against_dark	1.0	2.0
against_dragon	1.0	0.5
against_electric	0.5	1.0
against_fairy	1.0	0.5
against_fight	1.0	0.0
against_fire	1.0	2.0
against_flying	0.5	0.5
against_ghost	1.0	2.0
against_grass	1.0	0.5
against_ground	2.0	2.0
against_ice	1.0	0.5
against_normal	1.0	0.0
against_poison	1.0	0.0
against_psychic	1.0	0.5
against_rock	1.0	0.5
against_steel	0.5	0.5
against_water	1.0	1.0
attack	55	150
base_egg_steps	2560	5120
base_happiness	70	70
base_total	320	520
capture_rate	190	45
classification	Mouse Pokémon	Royal Sword Pokémon
defense	40	50
experience_growth	1000000	1000000
height_m	0.4	1.7
hp	35	60
japanese_name	Pikachu ピカチュウ	Gillgard ギルガルド
name	Pikachu	Aegislash
percentage_male	50.0	50.0
pokedex_number	25	681
sp_attack	50	150
sp_defense	50	50
speed	90	60
type1	electric	steel
type2	NaN	ghost
weight_kg	6.0	53.0

generation	1	6
is_legendary	0	0

	230	\
abilities	['Pickup', 'Sand Veil']	
against_bug	1.0	
against_dark	1.0	
against_dragon	1.0	
against_electric	0.0	
against_fairy	1.0	
against_fight	1.0	
against_fire	1.0	
against_flying	1.0	
against_ghost	1.0	
against_grass	2.0	
against_ground	1.0	
against_ice	2.0	
against_normal	1.0	
against_poison	0.5	
against_psychic	1.0	
against_rock	0.5	
against_steel	1.0	
against_water	2.0	
attack	60	
base_egg_steps	5120	
base_happiness	70	
base_total	330	
capture_rate	120	
classification	Long Nose Pokémon	
defense	60	
experience_growth	1000000	
height_m	0.5	
hp	90	
japanese_name	Gomazou ゴマゾウ	
name	Phanpy	
percentage_male	50.0	
pokedex_number	231	
sp_attack	40	
sp_defense	40	
speed	40	
type1	ground	
type2	NaN	
weight_kg	33.5	
generation	2	
is_legendary	0	

	46	\
abilities	['Effect Spore', 'Dry Skin', 'Damp']	
against_bug	2.0	

against_dark	1.0	
against_dragon	1.0	
against_electric	0.5	
against_fairy	1.0	
against_fight	0.5	
against_fire	4.0	
against_flying	4.0	
against_ghost	1.0	
against_grass	0.25	
against_ground	0.25	
against_ice	2.0	
against_normal	1.0	
against_poison	2.0	
against_psychic	1.0	
against_rock	2.0	
against_steel	1.0	
against_water	0.5	
attack	95	
base_egg_steps	5120	
base_happiness	70	
base_total	405	
capture_rate	75	
classification	Mushroom Pokémon	
defense	80	
experience_growth	1000000	
height_m	1.0	
hp	60	
japanese_name	Parasect パラセクト	
name	Parasect	
percentage_male	50.0	
pokedex_number	47	
sp_attack	60	
sp_defense	80	
speed	30	
type1	bug	
type2	grass	
weight_kg	29.5	
generation	1	
is_legendary	0	
	574	
abilities	['Frisk', 'Competitive', 'Shadow Tag']	
against_bug	2.0	
against_dark	2.0	
against_dragon	1.0	
against_electric	1.0	
against_fairy	1.0	
against_fight	0.5	
against_fire	1.0	

against_flying	1.0
against_ghost	2.0
against_grass	1.0
against_ground	1.0
against_ice	1.0
against_normal	1.0
against_poison	1.0
against_psychic	0.5
against_rock	1.0
against_steel	1.0
against_water	1.0
attack	45
base_egg_steps	5120
base_happiness	70
base_total	390
capture_rate	100
classification	Manipulate Pokémon
defense	70
experience_growth	1059860
height_m	0.7
hp	60
japanese_name	Gothimiru ゴチミル
name	Gothorita
percentage_male	24.6
pokedex_number	575
sp_attack	75
sp_defense	85
speed	55
type1	psychic
type2	NaN
weight_kg	18.0
generation	5
is_legendary	0

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 801 entries, 0 to 800
```

```
Data columns (total 41 columns):
```

#	Column	Non-Null Count	Dtype
0	abilities	801 non-null	object
1	against_bug	801 non-null	float64
2	against_dark	801 non-null	float64
3	against_dragon	801 non-null	float64
4	against_electric	801 non-null	float64
5	against_fairy	801 non-null	float64
6	against_fight	801 non-null	float64
7	against_fire	801 non-null	float64
8	against_flying	801 non-null	float64

9	against_ghost	801	non-null	float64
10	against_grass	801	non-null	float64
11	against_ground	801	non-null	float64
12	against_ice	801	non-null	float64
13	against_normal	801	non-null	float64
14	against_poison	801	non-null	float64
15	against_psychic	801	non-null	float64
16	against_rock	801	non-null	float64
17	against_steel	801	non-null	float64
18	against_water	801	non-null	float64
19	attack	801	non-null	int64
20	base_egg_steps	801	non-null	int64
21	base_happiness	801	non-null	int64
22	base_total	801	non-null	int64
23	capture_rate	801	non-null	object
24	classification	801	non-null	object
25	defense	801	non-null	int64
26	experience_growth	801	non-null	int64
27	height_m	781	non-null	float64
28	hp	801	non-null	int64
29	japanese_name	801	non-null	object
30	name	801	non-null	object
31	percentage_male	703	non-null	float64
32	pokedex_number	801	non-null	int64
33	sp_attack	801	non-null	int64
34	sp_defense	801	non-null	int64
35	speed	801	non-null	int64
36	type1	801	non-null	object
37	type2	417	non-null	object
38	weight_kg	781	non-null	float64
39	generation	801	non-null	int64
40	is_legendary	801	non-null	int64

dtypes: float64(21), int64(13), object(7)

memory usage: 256.7+ KB

df.describe().T

	count	mean	std	min
25%				
\				
against_bug	801.0	9.962547e-01	0.597248	0.25
0.5				
against_dark	801.0	1.057116e+00	0.438142	0.25
1.0				
against_dragon	801.0	9.687890e-01	0.353058	0.00
1.0				
against_electric	801.0	1.073970e+00	0.654962	0.00
0.5				
against_fairy	801.0	1.068976e+00	0.522167	0.25
1.0				
against_fight	801.0	1.065543e+00	0.717251	0.00

0.5					
against_fire	801.0	1.135456e+00	0.691853	0.25	
0.5					
against_flying	801.0	1.192884e+00	0.604488	0.25	
1.0					
against_ghost	801.0	9.850187e-01	0.558256	0.00	
1.0					
against_grass	801.0	1.034020e+00	0.788896	0.25	
0.5					
against_ground	801.0	1.098002e+00	0.738818	0.00	
1.0					
against_ice	801.0	1.208177e+00	0.735356	0.25	
0.5					
against_normal	801.0	8.870162e-01	0.266106	0.00	
1.0					
against_poison	801.0	9.753433e-01	0.549375	0.00	
0.5					
against_psychic	801.0	1.005306e+00	0.495183	0.00	
1.0					
against_rock	801.0	1.250312e+00	0.697148	0.25	
1.0					
against_steel	801.0	9.834582e-01	0.500117	0.25	
0.5					
against_water	801.0	1.058365e+00	0.606562	0.25	
0.5					
attack	801.0	7.785768e+01	32.158820	5.00	
55.0					
base_egg_steps	801.0	7.191011e+03	6558.220422	1280.00	
5120.0					
base_happiness	801.0	6.536205e+01	19.598948	0.00	
70.0					
base_total	801.0	4.283770e+02	119.203577	180.00	
320.0					
defense	801.0	7.300874e+01	30.769159	5.00	
50.0					
experience_growth	801.0	1.054996e+06	160255.835096	600000.00	
1000000.0					
height_m	781.0	1.163892e+00	1.080326	0.10	
0.6					
hp	801.0	6.895880e+01	26.576015	1.00	
50.0					
percentage_male	703.0	5.515576e+01	20.261623	0.00	
50.0					
pokedex_number	801.0	4.010000e+02	231.373075	1.00	
201.0					
sp_attack	801.0	7.130587e+01	32.353826	10.00	
45.0					
sp_defense	801.0	7.091136e+01	27.942501	20.00	
50.0					

speed	801.0	6.633458e+01	28.907662	5.00
45.0				
weight_kg	781.0	6.137810e+01	109.354766	0.10
9.0				
generation	801.0	3.690387e+00	1.930420	1.00
2.0				
is_legendary	801.0	8.739076e-02	0.282583	0.00
0.0				

	50%	75%	max
against_bug	1.0	1.0	4.0
against_dark	1.0	1.0	4.0
against_dragon	1.0	1.0	2.0
against_electric	1.0	1.0	4.0
against_fairy	1.0	1.0	4.0
against_fight	1.0	1.0	4.0
against_fire	1.0	2.0	4.0
against_flying	1.0	1.0	4.0
against_ghost	1.0	1.0	4.0
against_grass	1.0	1.0	4.0
against_ground	1.0	1.0	4.0
against_ice	1.0	2.0	4.0
against_normal	1.0	1.0	1.0
against_poison	1.0	1.0	4.0
against_psychic	1.0	1.0	4.0
against_rock	1.0	2.0	4.0
against_steel	1.0	1.0	4.0
against_water	1.0	1.0	4.0
attack	75.0	100.0	185.0
base_egg_steps	5120.0	6400.0	30720.0
base_happiness	70.0	70.0	140.0
base_total	435.0	505.0	780.0
defense	70.0	90.0	230.0
experience_growth	1000000.0	1059860.0	1640000.0
height_m	1.0	1.5	14.5
hp	65.0	80.0	255.0
percentage_male	50.0	50.0	100.0
pokedex_number	401.0	601.0	801.0
sp_attack	65.0	91.0	194.0
sp_defense	66.0	90.0	230.0
speed	65.0	85.0	180.0
weight_kg	27.3	64.8	999.9
generation	4.0	5.0	7.0
is_legendary	0.0	0.0	1.0

Data Preprocessing

Reordering name attribute

```
df.insert(0, 'name', df.pop('name'))  # done to easily identify names
df.head()
```

	name	abilities	against_bug	against_dark
0	Bulbasaur	['Overgrow', 'Chlorophyll']	1.0	1.0
1	Ivysaur	['Overgrow', 'Chlorophyll']	1.0	1.0
2	Venusaur	['Overgrow', 'Chlorophyll']	1.0	1.0
3	Charmander	['Blaze', 'Solar Power']	0.5	1.0
4	Charmeleon	['Blaze', 'Solar Power']	0.5	1.0

	against_dragon	against_electric	against_fairy	against_fight	\
0	1.0	0.5	0.5	0.5	
1	1.0	0.5	0.5	0.5	
2	1.0	0.5	0.5	0.5	
3	1.0	1.0	0.5	1.0	
4	1.0	1.0	0.5	1.0	

	against_fire	against_flying	...	percentage_male	pokedex_number
0	2.0	2.0	...	88.1	1
1	2.0	2.0	...	88.1	2
2	2.0	2.0	...	88.1	3
3	0.5	1.0	...	88.1	4
4	0.5	1.0	...	88.1	5

	sp_attack	sp_defense	speed	type1	type2	weight_kg	generation
0	65	65	45	grass	poison	6.9	1
1	80	80	60	grass	poison	13.0	1
2	122	120	80	grass	poison	100.0	1
3	60	50	65	fire	NaN	8.5	1

4	80	65	80	fire	NaN	19.0	1
---	----	----	----	------	-----	------	---

	is_legendary
--	--------------

0	0
1	0
2	0
3	0
4	0

[5 rows x 41 columns]

Null Values

```
df.isnull().sum()
```

name	0
abilities	0
against_bug	0
against_dark	0
against_dragon	0
against_electric	0
against_fairy	0
against_fight	0
against_fire	0
against_flying	0
against_ghost	0
against_grass	0
against_ground	0
against_ice	0
against_normal	0
against_poison	0
against_psychic	0
against_rock	0
against_steel	0
against_water	0
attack	0
base_egg_steps	0
base_happiness	0
base_total	0
capture_rate	0
classification	0
defense	0
experience_growth	0
height_m	20
hp	0
japanese_name	0
percentage_male	98
pokedex_number	0
sp_attack	0

sp_defense	0
speed	0
type1	0
type2	384
weight_kg	20
generation	0
is_legendary	0

dtype: int64

"height_m" and "weight_kg" has 20-20 Null Values each. "percentage_male" has 98 Null Values
 "type2" has 384 missing values

Data Imputation

```
# Replacing missing height_m and weight_kg values with mode of them
df["height_m"].fillna(df["height_m"].mean(), inplace=True)
df["weight_kg"].fillna(df["weight_kg"].mean(), inplace=True)
```

```
# Replacing the missing values in percentage_male with None
df["percentage_male"].fillna('None', inplace=True)
```

```
# Replacing the missing values in type 2 with NULL
df["type2"].fillna('None', inplace=True)
```

```
df.isnull().sum()
```

name	0
abilities	0
against_bug	0
against_dark	0
against_dragon	0
against_electric	0
against_fairy	0
against_fight	0
against_fire	0
against_flying	0
against_ghost	0
against_grass	0
against_ground	0
against_ice	0
against_normal	0
against_poison	0
against_psychic	0
against_rock	0
against_steel	0
against_water	0
attack	0
base_egg_steps	0
base_happiness	0
base_total	0

```

capture_rate      0
classification    0
defense           0
experience_growth 0
height_m          0
hp               0
japanese_name     0
percentage_male   0
pokedex_number    0
sp_attack         0
sp_defense        0
speed            0
type1            0
type2            0
weight_kg         0
generation        0
is_legendary      0
dtype: int64

```

capture_rate attribute

capture_rate is an object attribute but has numerical values. Now, lets check the capture_rate attribute.

```

for i in df.capture_rate:
    print(i, end=", ")

```

45, 45, 45, 45, 45, 45, 45, 45, 45, 255, 120, 45, 255, 120, 45, 255, 120, 45, 255, 127, 255, 90, 255, 90, 190, 75, 255, 90, 235, 120, 45, 235, 120, 45, 150, 25, 190, 75, 170, 50, 255, 90, 255, 120, 45, 190, 75, 190, 75, 255, 50, 255, 90, 190, 75, 190, 75, 190, 75, 255, 120, 45, 200, 100, 50, 180, 90, 45, 255, 120, 45, 190, 60, 255, 120, 45, 190, 60, 190, 75, 190, 60, 45, 190, 45, 190, 75, 190, 75, 190, 60, 190, 90, 45, 45, 190, 75, 225, 60, 190, 60, 90, 45, 190, 75, 45, 45, 45, 190, 60, 120, 60, 30, 45, 45, 225, 75, 225, 60, 225, 60, 45, 45, 45, 45, 45, 45, 255, 45, 45, 35, 45, 45, 45, 45, 45, 45, 45, 45, 45, 45, 25, 3, 3, 3, 45, 45, 45, 3, 45, 45, 45, 45, 45, 45, 45, 45, 45, 45, 45, 255, 90, 255, 90, 255, 90, 255, 90, 90, 190, 75, 190, 150, 170, 190, 75, 190, 75, 235, 120, 45, 45, 190, 75, 65, 45, 255, 120, 45, 45, 235, 120, 75, 255, 90, 45, 45, 30, 70, 45, 225, 45, 60, 190, 75, 190, 60, 25, 190, 75, 45, 25, 190, 45, 60, 120, 60, 190, 75, 225, 75, 60, 190, 75, 45, 25, 25, 120, 45, 45, 120, 60, 45, 45, 45, 75, 45, 45, 45, 45, 45, 30, 3, 3, 3, 45, 45, 45, 3, 3, 45, 45, 45, 45, 45, 45, 45, 45, 45, 45, 45, 255, 127, 255, 90, 255, 120, 45, 120, 45, 255, 120, 45, 255, 120, 45, 200, 45, 190, 45, 235, 120, 45, 200, 75, 255, 90, 255, 120, 45, 255, 120, 45, 190, 120, 45, 180, 200, 150, 255, 255, 60, 45, 45, 180, 90, 45, 180, 90, 120, 45, 200, 200, 150, 150, 150, 225, 75, 225, 60, 125, 60, 255, 150, 90, 255, 60, 255, 255, 120, 45, 190, 60, 255, 45, 90, 90, 45, 45, 190, 75, 205, 155, 255, 90, 45, 45, 45,

45, 255, 60, 45, 200, 225, 45, 190, 90, 200, 45, 30, 125, 190, 75, 255, 120, 45, 255, 60, 60, 25, 225, 45, 45, 45, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 45, 3, 3, 45, 45, 45, 45, 45, 45, 45, 45, 255, 120, 45, 255, 127, 255, 45, 235, 120, 45, 255, 75, 45, 45, 45, 45, 120, 45, 45, 120, 45, 200, 190, 75, 190, 75, 190, 75, 45, 125, 60, 190, 60, 45, 30, 190, 75, 120, 225, 60, 255, 90, 255, 145, 130, 30, 100, 45, 45, 45, 50, 75, 45, 140, 60, 120, 45, 140, 75, 200, 190, 75, 25, 120, 60, 45, 30, 30, 30, 30, 30, 30, 30, 30, 45, 45, 30, 50, 30, 45, 60, 45, 75, 45, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 30, 3, 3, 45, 3, 3, 45, 45, 45, 45, 45, 45, 45, 45, 255, 255, 255, 120, 45, 255, 90, 190, 75, 190, 75, 190, 75, 190, 75, 255, 120, 45, 190, 75, 255, 120, 45, 190, 45, 120, 60, 255, 180, 90, 45, 255, 120, 45, 45, 45, 255, 120, 45, 255, 120, 45, 190, 75, 190, 75, 25, 180, 90, 45, 120, 60, 255, 190, 75, 180, 90, 45, 190, 90, 45, 45, 45, 45, 190, 60, 75, 45, 255, 60, 200, 100, 50, 200, 100, 50, 190, 45, 255, 120, 45, 190, 75, 200, 200, 75, 190, 75, 190, 60, 75, 190, 75, 255, 90, 130, 60, 30, 190, 60, 30, 255, 90, 190, 90, 45, 75, 60, 45, 120, 60, 25, 200, 75, 75, 180, 45, 45, 190, 90, 120, 45, 45, 190, 60, 190, 60, 90, 90, 45, 45, 45, 45, 15, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 45, 45, 45, 45, 45, 45, 45, 45, 45, 255, 127, 255, 120, 45, 255, 120, 45, 220, 65, 225, 120, 45, 200, 45, 220, 65, 160, 190, 75, 180, 90, 45, 200, 140, 200, 140, 190, 80, 120, 45, 225, 55, 225, 55, 190, 75, 45, 45, 45, 45, 45, 100, 180, 60, 45, 45, 45, 75, 120, 60, 120, 60, 190, 55, 190, 45, 45, 45, 3, 3, 3, 3, 45, 45, 45, 45, 45, 45, 45, 45, 45, 255, 120, 45, 255, 127, 255, 120, 45, 225, 60, 45, 190, 75, 190, 90, 60, 190, 75, 190, 60, 200, 100, 190, 75, 190, 75, 120, 45, 140, 70, 235, 120, 45, 60, 45, 45, 90, 45, 140, 60, 60, 3, 3, 30 (Meteorite) 255 (Core), 45, 70, 180, 45, 80, 70, 25, 45, 45, 45, 3, 3, 3, 3, 45, 45, 45, 45, 45, 25, 255, 30, 25, 255, 15, 3, 3,

```
df[df["capture_rate"]=="30 (Meteorite)255 (Core)"]
```

	name	abilities	against_bug	against_dark
against_dragon	\			
773	Minior	['Shields Down']	0.5	1.0
1.0				

	against_electric	against_fairy	against_fight	against_fire	\
773	2.0	1.0	1.0	0.5	

against_flying	...	percentage_male	pokedex_number
sp_attack \			
773	0.5	...	None
			774
			100

	sp_defense	speed	type1	type2	weight_kg	generation
is_legendary						
773	60	120	rock	flying	40.0	7
0						

```
[1 rows x 41 columns]
```

As we can see in the output values there is one value "30 (Meteorite)255 (Core)". We know its a rock/fly type pokemon, therefore, we will replace it with "Meteorite" capture_rate of 30.

```
# replacing with 30
df["capture_rate"].replace({"30 (Meteorite)255 (Core)": "30"},
inplace=True)

# converting into integer type attribute
df["capture_rate"] = df["capture_rate"].astype('int')
df["capture_rate"].dtype

dtype('int64')
```

Dropping unnecessary attributes

We will drop off 3 unnecessary columns:

1. japanese_name
2. pokedex_number
3. percentage_male

```
df.drop(columns=['japanese_name', 'pokedex_number',
'percentage_male'], axis=1, inplace=True)
```

Combining number of abilities and type1 & type2

```
# adding total abilities that a pokemon has
df["tot_abilities"] = df.apply(lambda x: len(x["abilities"]), axis=1)

# merging type1 and type2 and adding into new column=> type,
# and renaming type1 to primary and type2 to secondary
df['type'] = df.apply(lambda x: x['type1'] if pd.isnull(x['type2'])
else f'{x["type1"]}_{x["type2"]}', axis=1)
df.rename(columns = {'type1':'primary type', 'type2':'secondary
type'}, inplace = True)

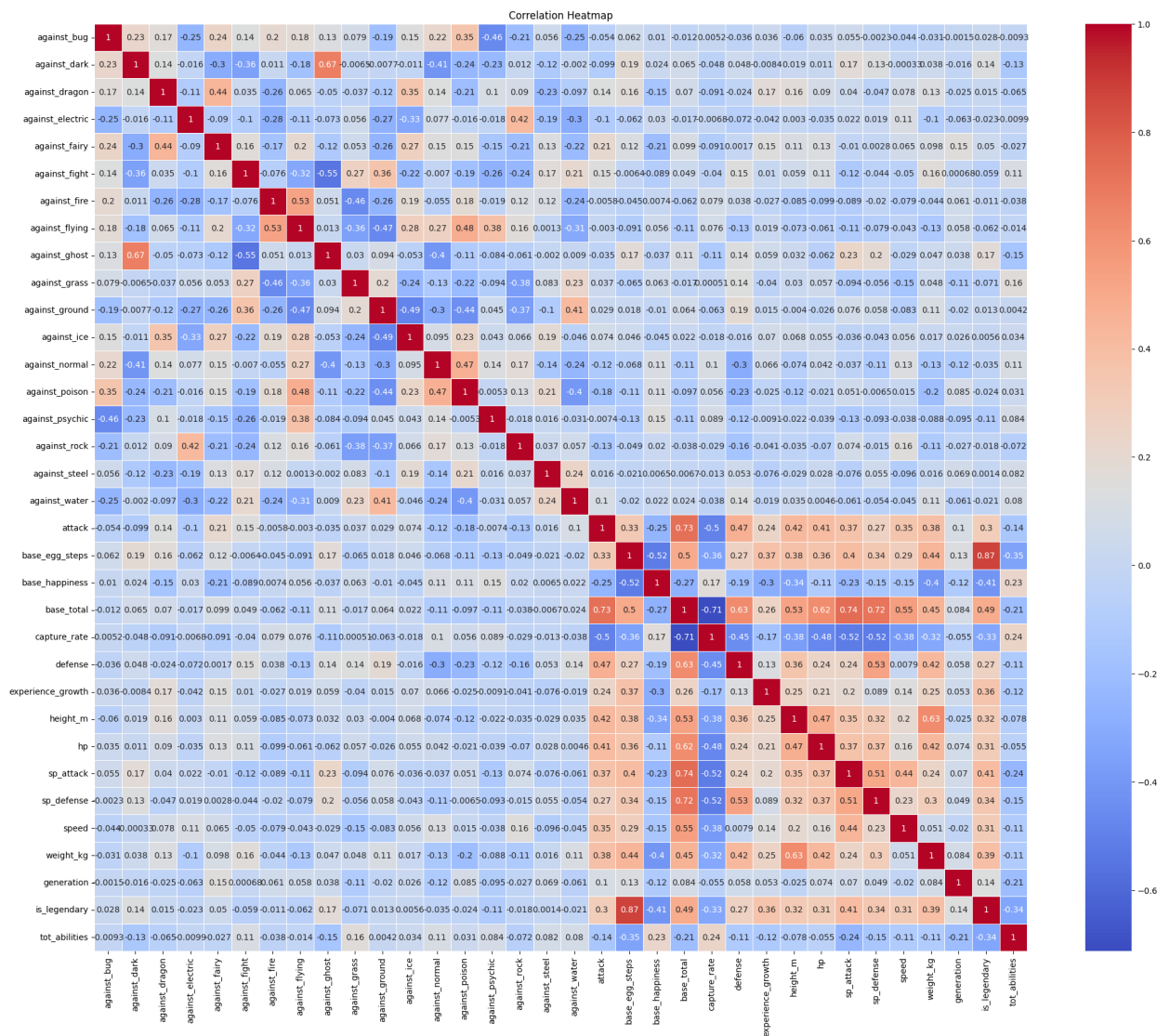
# Checking the final shape of df before moving into visualizations
df.shape

(801, 40)
```

Data Analysis

```
plt.figure(figsize=(25, 20))
sns.heatmap(df.corr(numeric_only=True), annot=True, cmap='coolwarm',
```

```
linewidths=0.5).set_title("Correlation Heatmap")
plt.show()
```



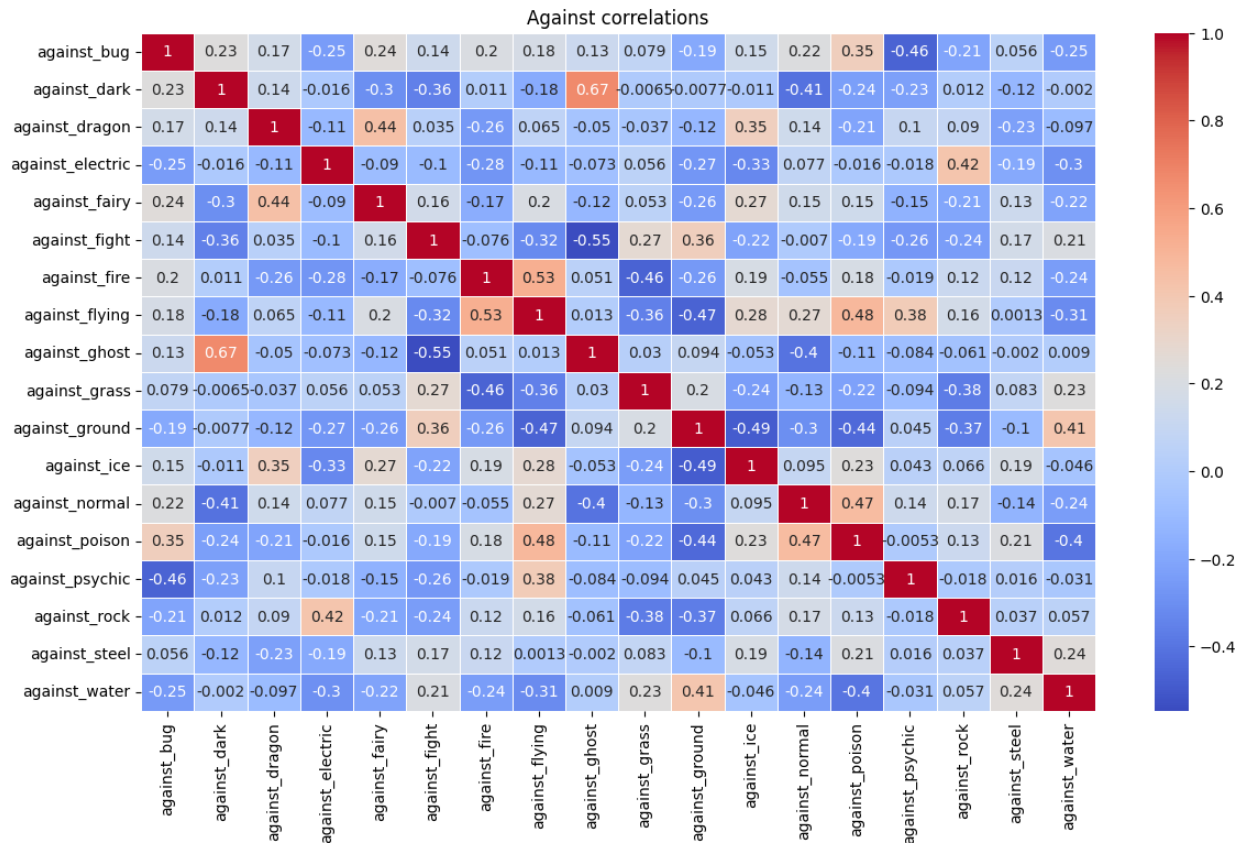
Lets distribute the correlation into two main parts for proper understanding =>

```
against=[]
rest=[]
for i in df.columns:
    if 'against' in i:
        against.append(i)
    else:
        rest.append(i)

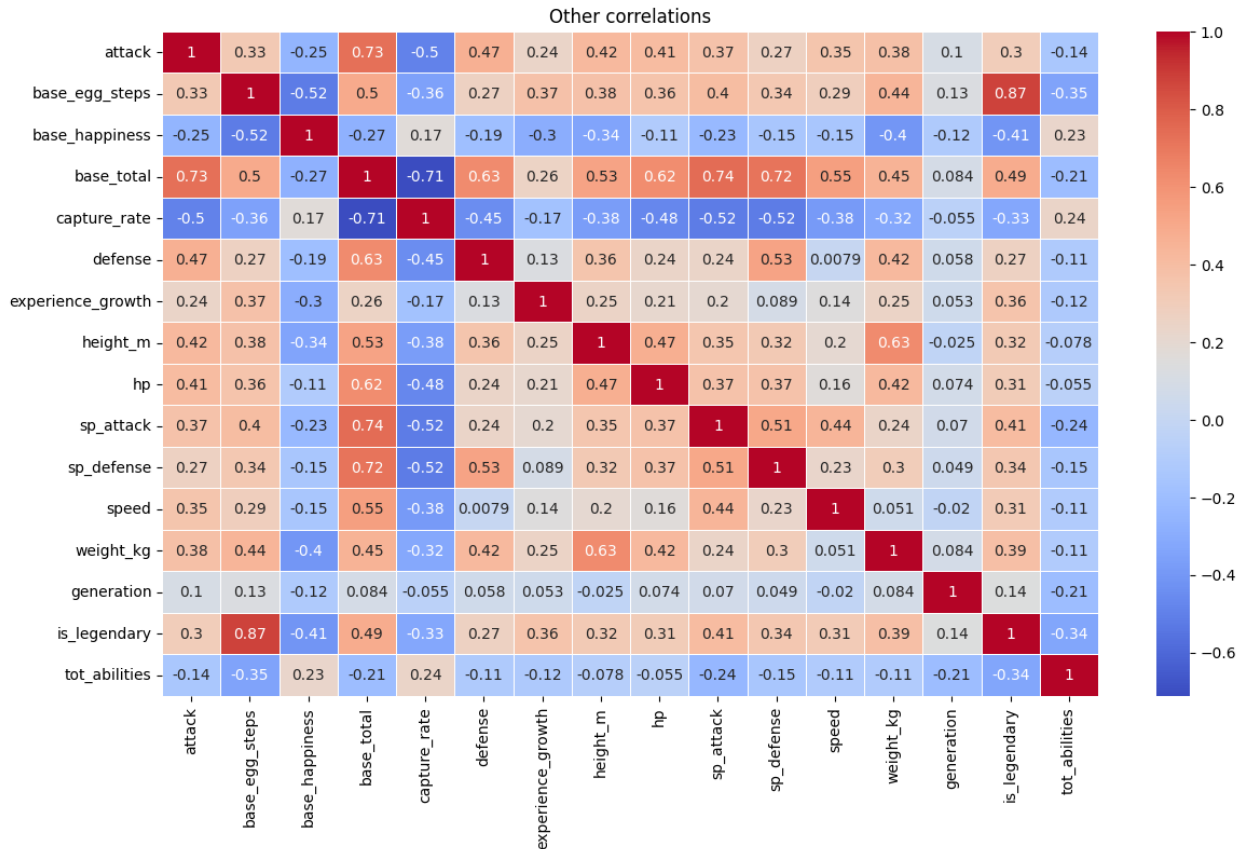
plt.figure(figsize=(14, 8))
sns.heatmap(df[against].corr(), annot=True, cmap='coolwarm',
```



```
linewidths=0.5).set_title("Against correlations")
plt.show()
```



```
plt.figure(figsize=(14, 8))
sns.heatmap(df[rest].corr(numeric_only=True), annot=True,
            cmap='coolwarm', linewidths=0.5).set_title("Other correlations")
plt.show()
```



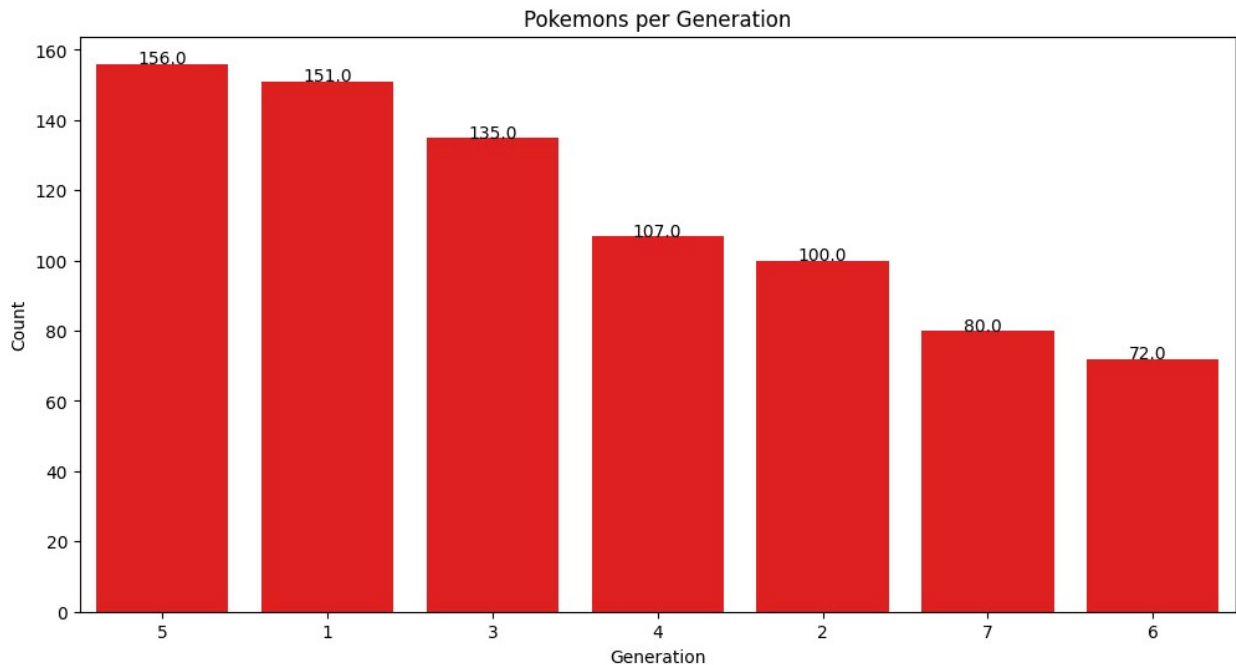
Now we can see from the above heatmap, following relations:

- base_total has good correlation with attack, defense, sp_attack, and sp_defense.
- base_egg_steps have a huge correlation with is_legendary attribute.
- weight_kg is also very correlated with height_m

Visualizations

1. Count of Pokemons per generation

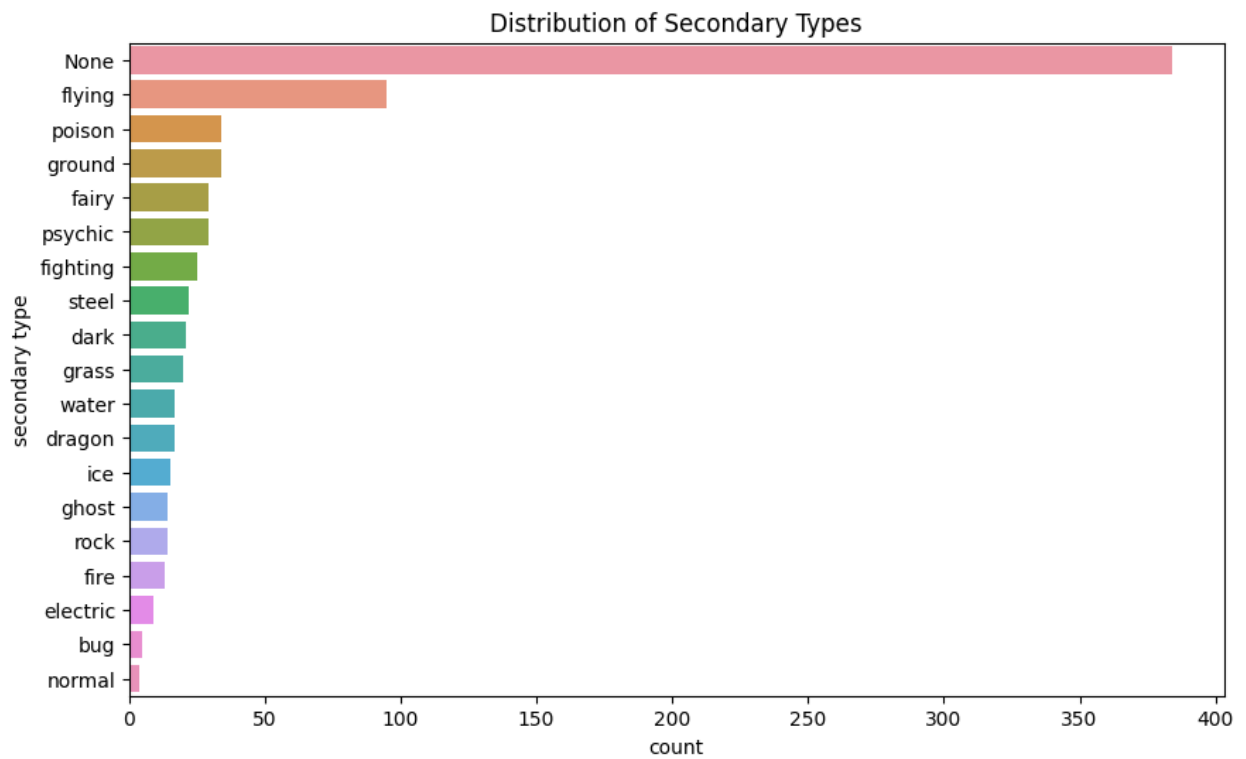
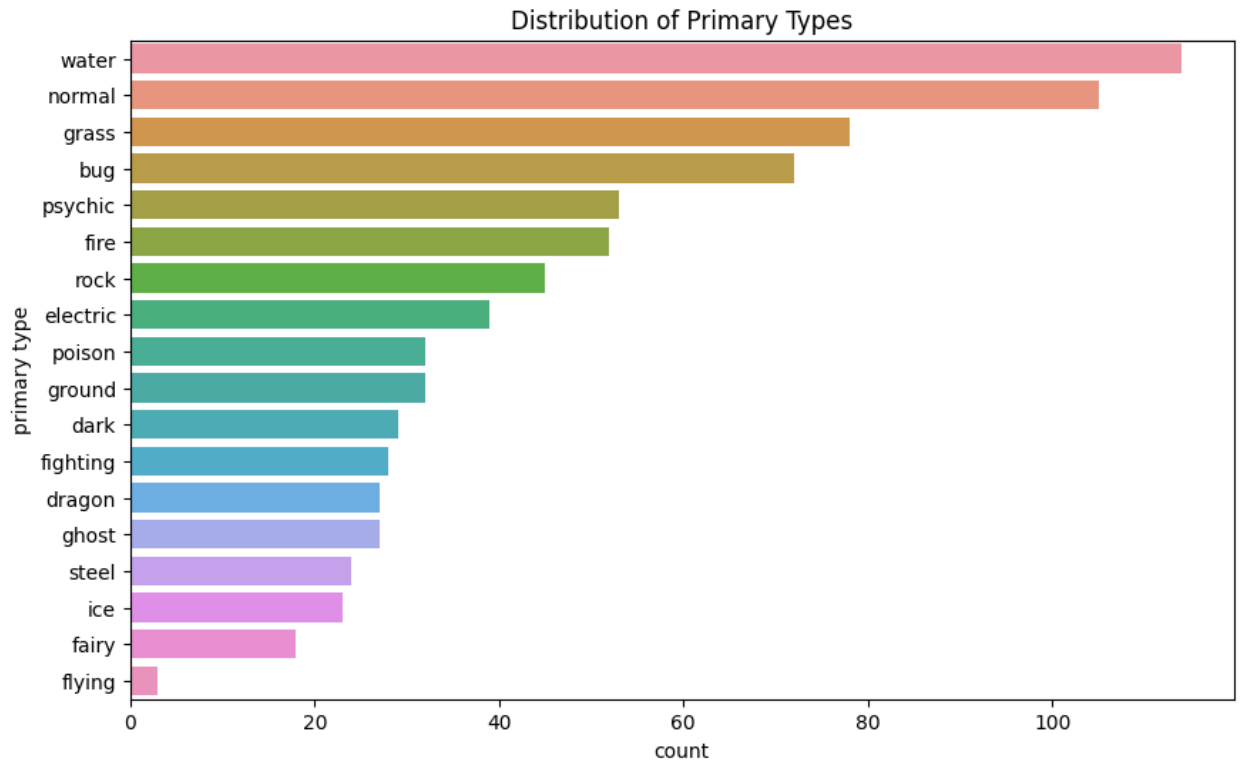
```
plt.figure(figsize=(12,6))
ax =
sns.countplot(x='generation',data=df,order=df['generation'].value_counts().index,color='red')
ax.set_title('Pokemons per Generation')
ax.set_xlabel('Generation',ylabel='Count')
for p in ax.patches:
    ax.annotate('{:.1f}'.format(p.get_height()), (p.get_x()+0.25,
p.get_height()+0.01))
plt.show()
```



2. Distribution of Primary and Secondary Types of pokemon

```
# Bar charts for primary type
plt.figure(figsize=(10, 6))
sns.countplot(y='primary type', data=df, order=df['primary
type'].value_counts().index)
plt.title('Distribution of Primary Types')
plt.show()

# Bar charts for secondary type
plt.figure(figsize=(10, 6))
sns.countplot(y='secondary type', data=df, order=df['secondary
type'].value_counts().index)
plt.title('Distribution of Secondary Types')
plt.show()
```



From the above plot, we can derive following conclusions:

- Most occurred pokemon type

- Primary type = Water Type
 - Secondary type = None; followed by flying type
- Least occurred pokemon type
 - Primary type = flying
 - Secondary type = normal

3. Types of Pokemons in each Generation

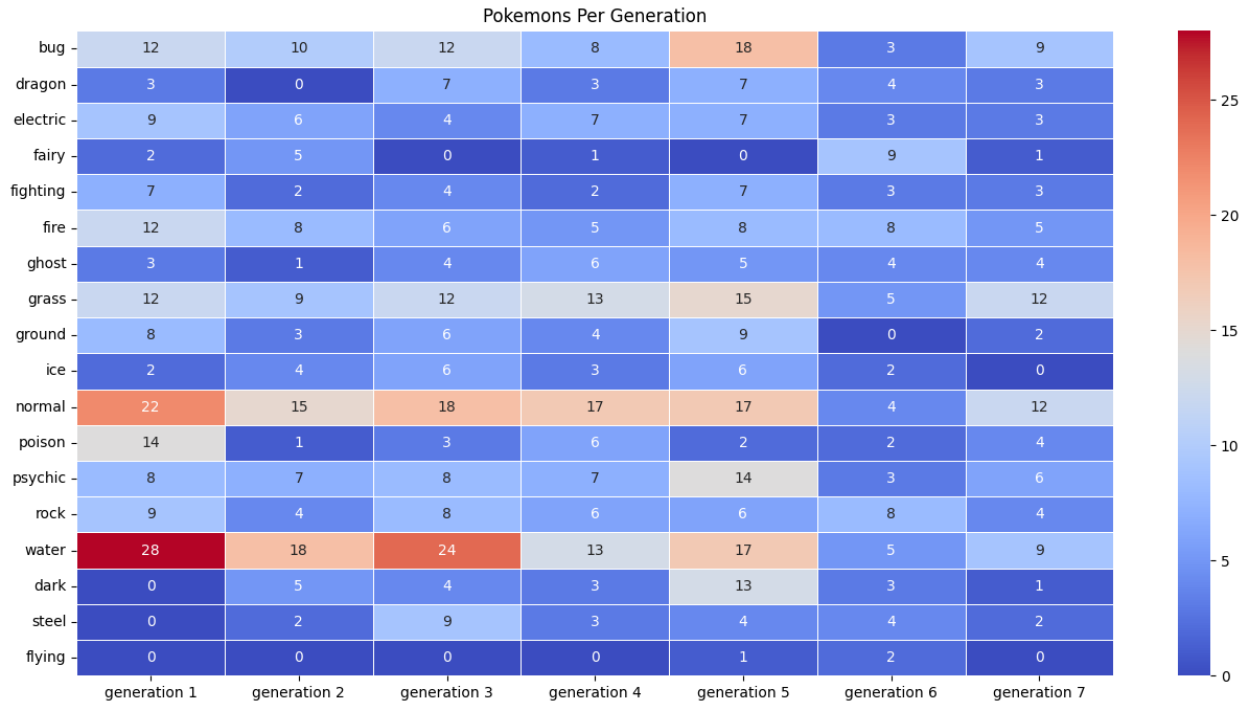
```

primary_type_generation_group = df.groupby(['generation', 'primary
type'])['name'].count().to_frame().reset_index()
primary_type_generation_group.rename(columns={'name' : 'name_count'},
inplace=True)
primary_type_generation_dict = {}
for generation in
list(primary_type_generation_group['generation'].unique()):
    current_generation = []
    for p_type in primary_type_generation_group['primary
type'].unique():
        try:
            current_generation.append(

primary_type_generation_group.loc[(primary_type_generation_group['gene
ration']==generation)
&
(primary_type_generation_group['primary type'] == p_type)]
['name_count'].values[0])
        except IndexError:
            current_generation.append(0)
    primary_type_generation_dict[f'generation {generation}'] =
current_generation

p_type_by_generation = pd.DataFrame(primary_type_generation_dict,
index= primary_type_generation_group['primary type'].unique())
fig, axes = plt.subplots(figsize=(16,8))
sns.heatmap(p_type_by_generation, annot=True, cmap='coolwarm',
linewidths=0.5).set_title('Pokemons Per Generation')
plt.show()

```



As we can see that, not each generation have all types of pokemons: And we can derive following conclusions from above::

- Only Gen 5 & 6 have flying type pokemons
- In Gen 1, there is no dark, steel & flying type pokemons
- In Gen 1, 2, & 3, water type pokemons are most common
- In Gen 4, normal type pokemons are most common
- In Gen 5, bug type pokemons are most common
- In Gen 6, fairy type pokemons are most common
- In Gen 7, normal & grass type pokemons are most common

4. Easiest / Hardest Pokemon Type to catch

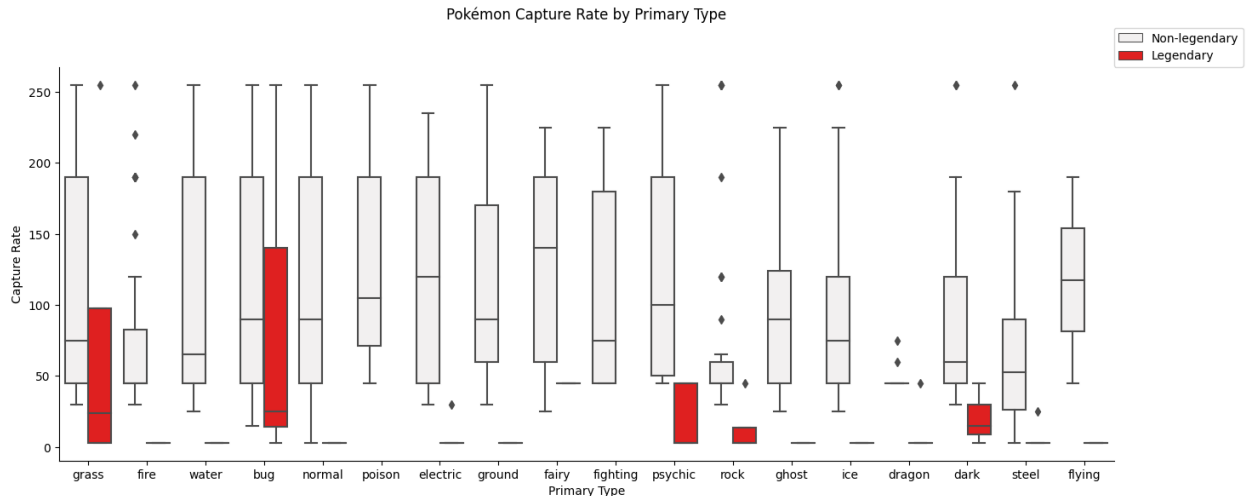
```
plt.figure(figsize=(16,6))
ax = sns.boxplot(x='primary type',y='capture_rate',
hue='is_legendary', data = df, color="red")

ax.set_xlabel(xlabel='Primary Type')
ax.set_ylabel(ylabel='Capture Rate')
ax.set_title('Pokémon Capture Rate by Primary Type', pad=40)

sns.despine(top=True, right=True)

handles, labels = ax.get_legend_handles_labels()
ax.legend(handles, ['Non-legendary', 'Legendary'], loc=(1,1))

<matplotlib.legend.Legend at 0x7cee17d88850>
```

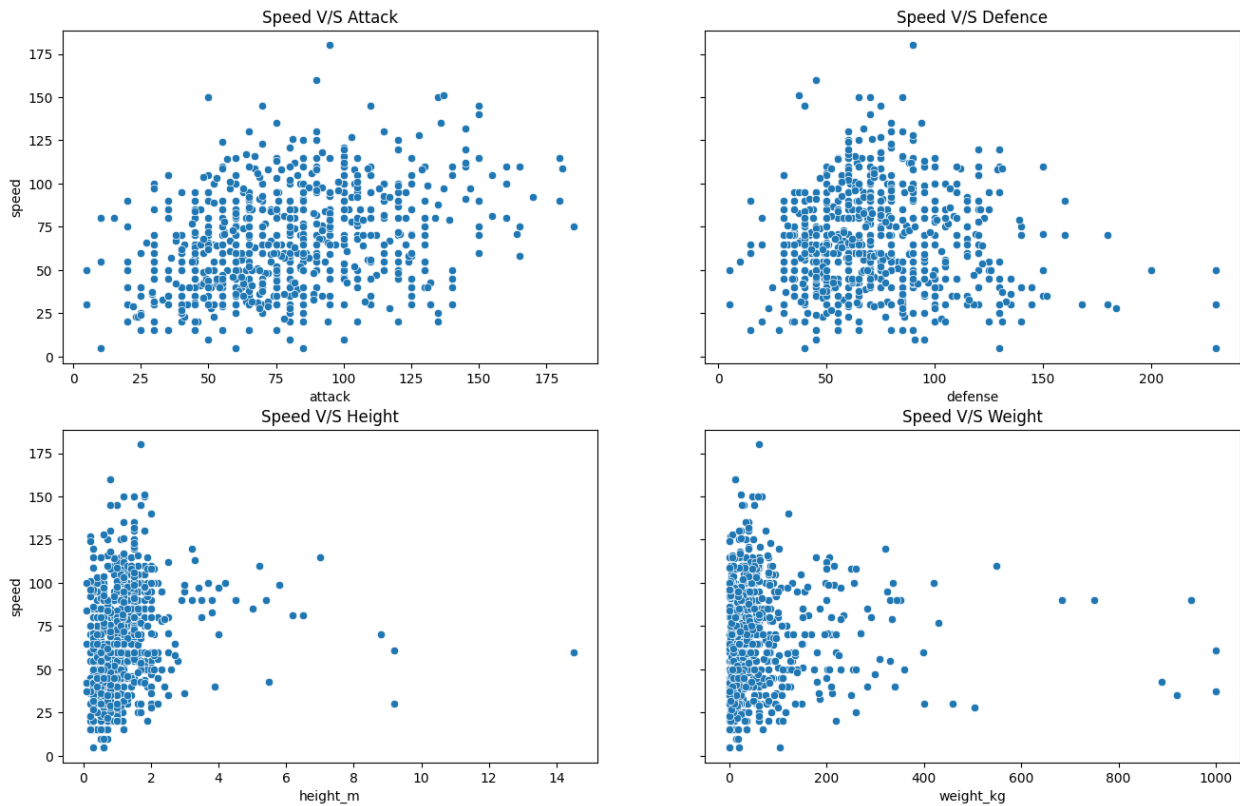


The easiest pokemon type to catch is "fairy" and hardest to catch is "dragon" type. It is also hard to catch "rock" and "fire" type pokemons. In legendary pokemons, easiest to catch are from "bug" and "grass" types.

5. How Speed correlate with various base stats?

```
fig, axes = plt.subplots(2, 2, figsize=(16, 10), sharey=True)
sns.scatterplot(x='attack', y='speed', data=df, ax=axes[0, 0])
axes[0, 0].set_title("Speed V/S Attack")
sns.scatterplot(x='defense', y='speed', data=df, ax=axes[0, 1])
axes[0, 1].set_title("Speed V/S Defence")
sns.scatterplot(x='height_m', y='speed', data=df, ax=axes[1, 0])
axes[1, 0].set_title("Speed V/S Height")
sns.scatterplot(x='weight_kg', y='speed', data=df, ax=axes[1, 1])
axes[1, 1].set_title("Speed V/S Weight")
fig.suptitle("Speed Factor?", size=20)
plt.show()
```

Speed Factor?



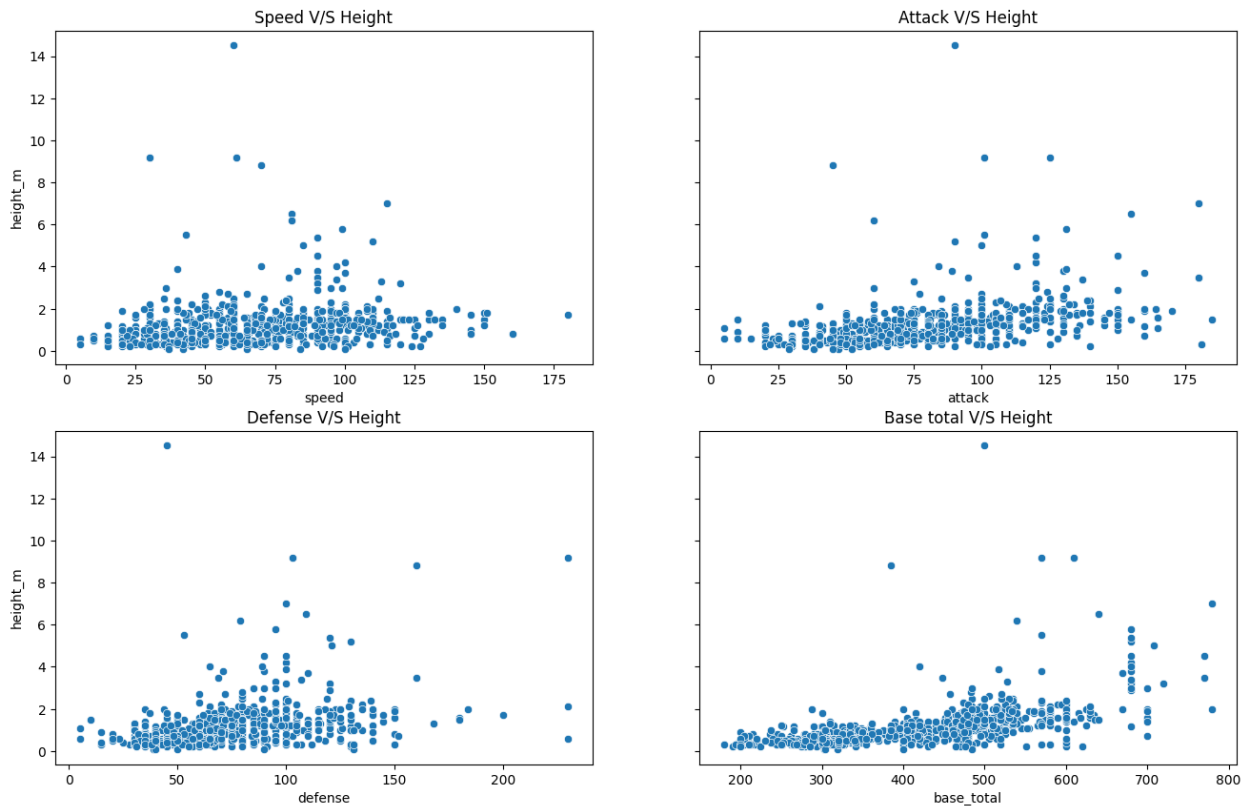
Insights from the above plots:

- For most pokemons, Attack capacity slightly depends on its speed
- For most pokemons, Defense also slightly depends on its speed
- Height of pokemons highly affects the speed (Less Height --> High speed)
- Weight of pokemons also affects the speed (Less Weight --> High speed)

6. How Height correlate with various base stats?

```
fig, axes = plt.subplots(2, 2, figsize=(16, 10), sharey=True)
sns.scatterplot(x='speed', y='height_m', data=df, ax=axes[0, 0])
axes[0, 0].set_title("Speed V/S Height")
sns.scatterplot(x='attack', y='height_m', data=df, ax=axes[0, 1])
axes[0, 1].set_title("Attack V/S Height")
sns.scatterplot(x='defense', y='height_m', data=df, ax=axes[1, 0])
axes[1, 0].set_title("Defense V/S Height")
sns.scatterplot(x='base_total', y='height_m', data=df, ax=axes[1, 1])
axes[1, 1].set_title("Base total V/S Height")
fig.suptitle("Height Factor?", size=20)
plt.show()
```


Height Factor?



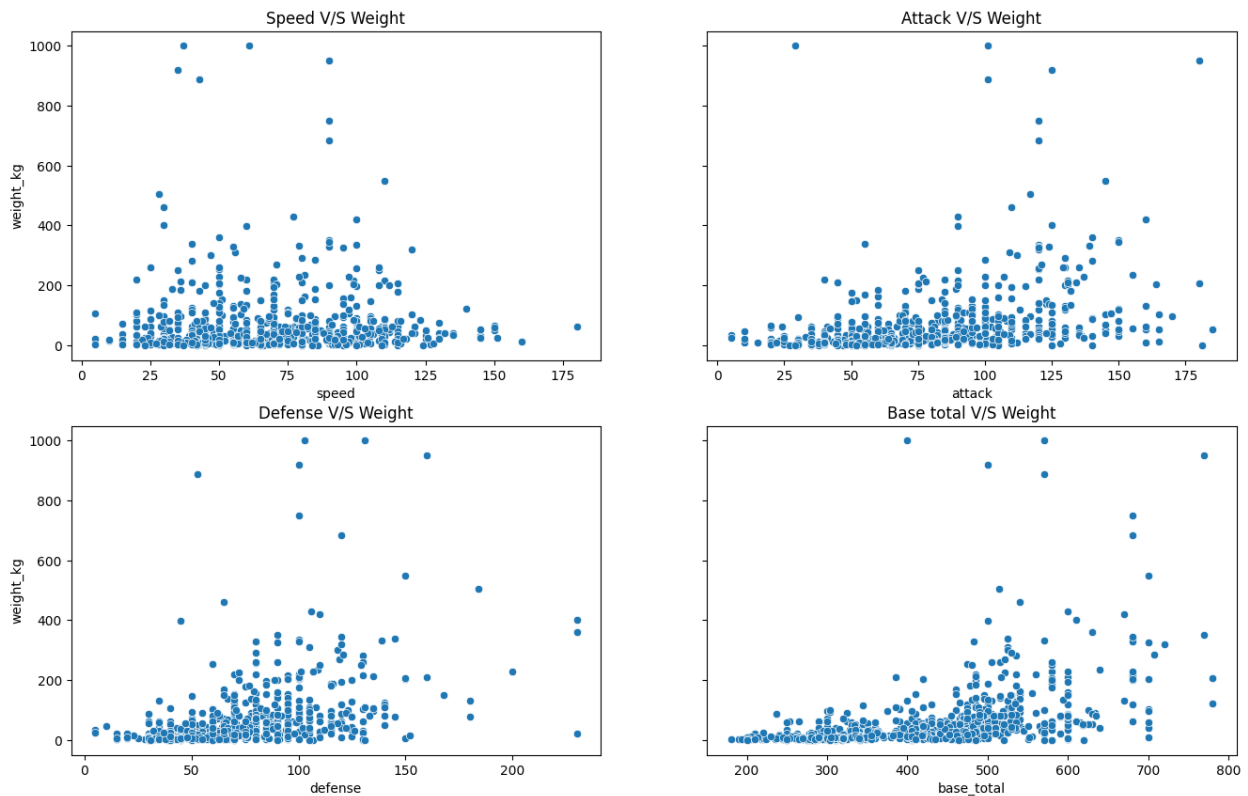
Insights from the above plots:

- Height of pokemons highly affects the speed (Less Height --> High speed)
- Height also highly affects attack capacity (less height --> high attack power)
- For most pokemons, Defense moderately correlates to Height
- Also, we can see that some pokemons with moderate height have high base total

7. How Weight correlate with various base stats?

```
fig, axes = plt.subplots(2, 2, figsize=(16, 10), sharey=True)
sns.scatterplot(x='speed', y='weight_kg', data=df, ax=axes[0, 0])
axes[0, 0].set_title("Speed V/S Weight")
sns.scatterplot(x='attack', y='weight_kg', data=df, ax=axes[0, 1])
axes[0, 1].set_title("Attack V/S Weight")
sns.scatterplot(x='defense', y='weight_kg', data=df, ax=axes[1, 0])
axes[1, 0].set_title("Defense V/S Weight")
sns.scatterplot(x='base_total', y='weight_kg', data=df, ax=axes[1, 1])
axes[1, 1].set_title("Base total V/S Weight")
fig.suptitle("Weight Factor?", size=20)
plt.show()
```

Weight Factor?

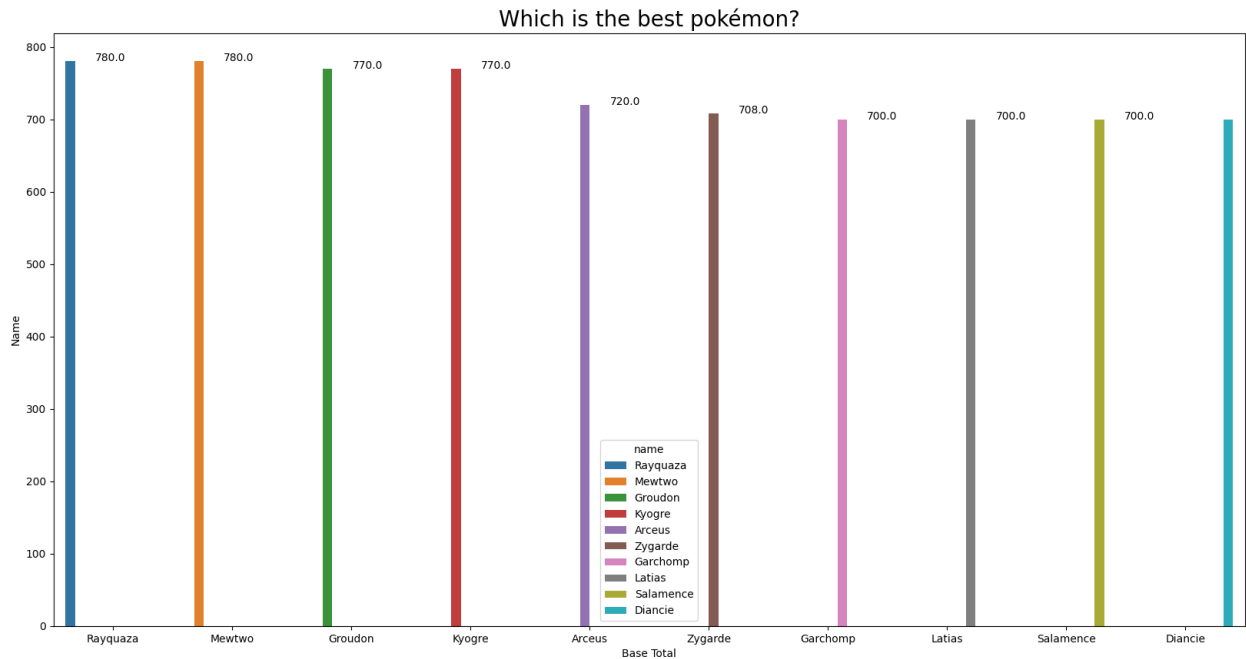


Insights from the above plots:

- High-weight pokemons are slower, while low-weight ones are faster. Some high-weight Pokemon have more speed, likely flying types.
- Heavyweight pokemons have better attack power,
- Moderate weight can increase defense strength
- A strong base total, weighing 100-200kgs, signifies a pokemon's strength.

8. Strongest Pokemon

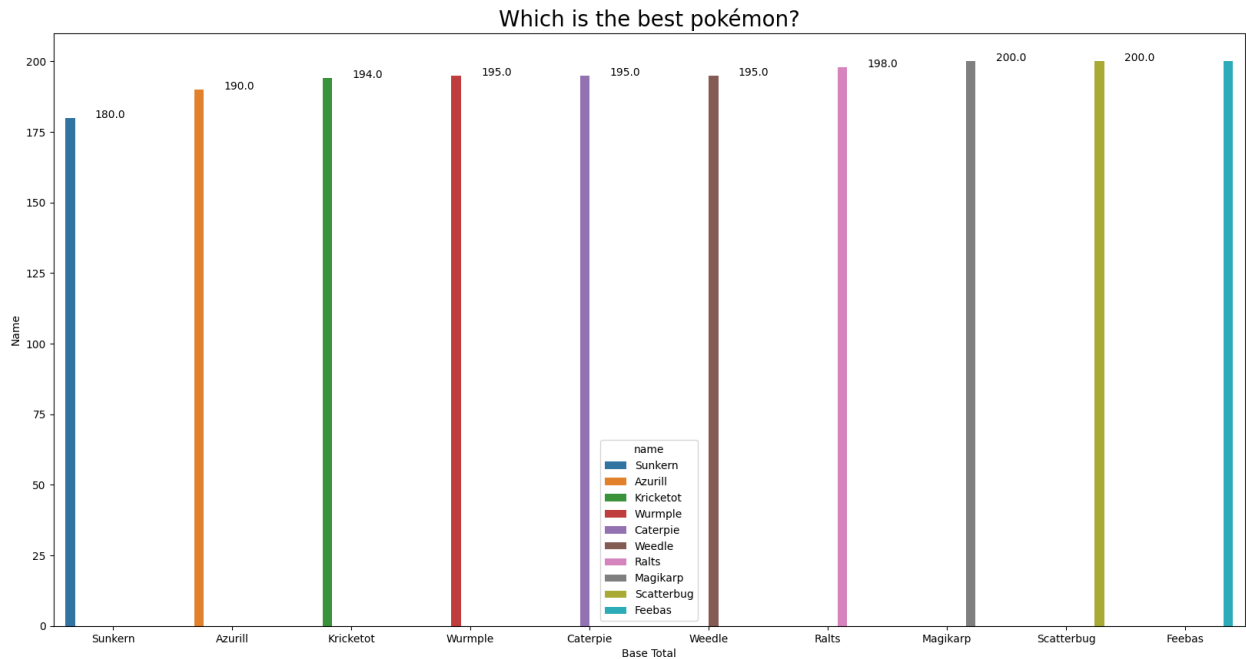
```
top10_pokemon_base_total = df.sort_values(by="base_total",
ascending=False).reset_index()[:10]
plt.figure(figsize=(20,10))
ax = sns.barplot(x=top10_pokemon_base_total["name"],
y=top10_pokemon_base_total["base_total"], orient='v',
hue=top10_pokemon_base_total["name"])
ax.set_title("Which is the best pokémon?", size=20)
ax.set(xlabel="Base Total", ylabel="Name")
for p in ax.patches:
    ax.annotate('{:.1f}'.format( p.get_height()), (p.get_x()+0.25,
p.get_height()+0.01))
```



SO, the strongest pokemons being Mewtwo, Rayquaza, followed by Groudon, Kyogre, and others.

9. Weakest Pokemon

```
top10_pokemon_base_total = df.sort_values(by="base_total",
ascending=True).reset_index()[:10]
plt.figure(figsize=(20,10))
ax = sns.barplot(x=top10_pokemon_base_total["name"],
y=top10_pokemon_base_total["base_total"], orient='v',
hue=top10_pokemon_base_total["name"])
ax.set_title("Which is the best pokémon?", size=20)
ax.set(xlabel="Base Total", ylabel="Name")
for p in ax.patches:
    ax.annotate('{:.1f}'.format( p.get_height()), (p.get_x()+0.25,
p.get_height()+0.01))
```



So, the weakest pokemon is Sunkern, followed by Azurill, Kricketot, and others.

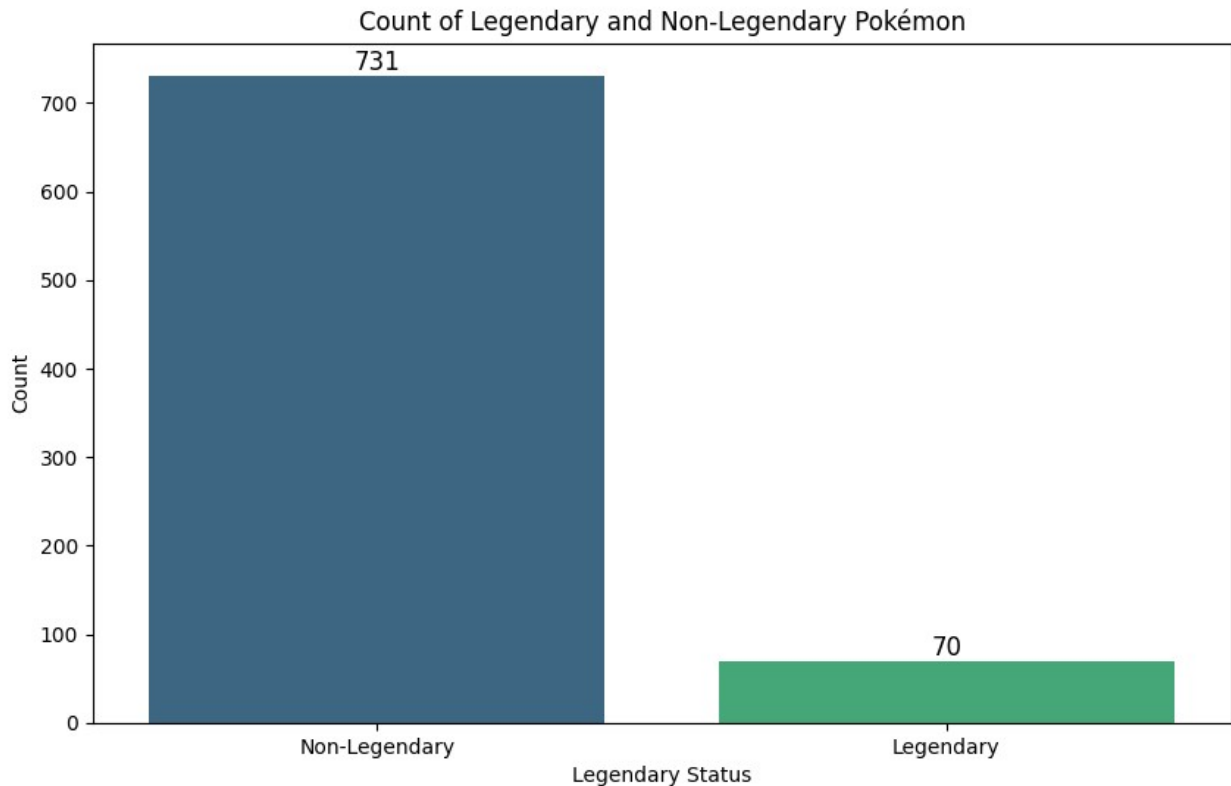
10. Count of legendary pokemons

```
legendary_counts = df['is_legendary'].value_counts()

plt.figure(figsize=(10, 6))
bar = sns.barplot(x=legendary_counts.index, y=legendary_counts.values,
                  palette="viridis")
plt.xlabel('Legendary Status')
plt.ylabel('Count')
plt.title('Count of Legendary and Non-Legendary Pokémon')
plt.xticks(ticks=[0, 1], labels=['Non-Legendary', 'Legendary'])

for i in range(len(legendary_counts)):
    bar.text(i, legendary_counts.values[i] + 0.1,
             legendary_counts.values[i], ha='center', va='bottom', fontsize=12)

plt.show()
```



11. What is the most common type among legendary pokemons?

```
# Filter for legendary Pokémon
legendary_pokemon = df[df['is_legendary']==1]

# Count primary and secondary types
primary_type_counts = legendary_pokemon['primary type'].value_counts()
secondary_type_counts = legendary_pokemon['secondary
type'].value_counts(dropna=False)

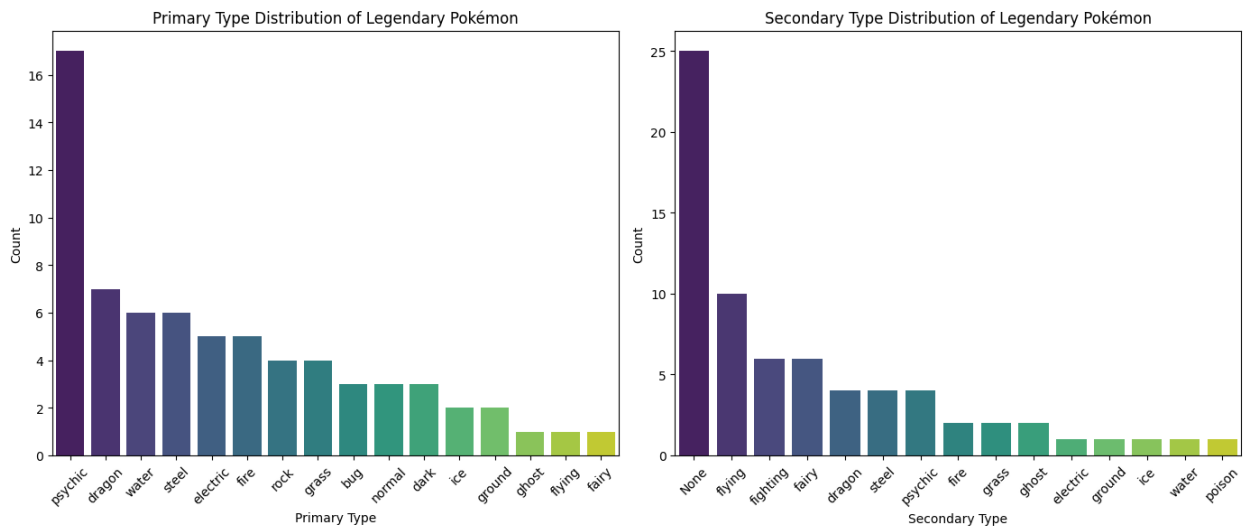
# Plot the distribution of primary types
plt.figure(figsize=(14, 6))

plt.subplot(1, 2, 1)
sns.barplot(x=primary_type_counts.index, y=primary_type_counts.values,
palette="viridis")
plt.xlabel('Primary Type')
plt.ylabel('Count')
plt.title('Primary Type Distribution of Legendary Pokémon')
plt.xticks(rotation=45)

# Plot the distribution of secondary types
plt.subplot(1, 2, 2)
sns.barplot(x=secondary_type_counts.index,
y=secondary_type_counts.values, palette="viridis")
plt.xlabel('Secondary Type')
```

```
plt.ylabel('Count')
plt.title('Secondary Type Distribution of Legendary Pokémon')
plt.xticks(rotation=45)

# Adjust layout
plt.tight_layout()
plt.show()
```

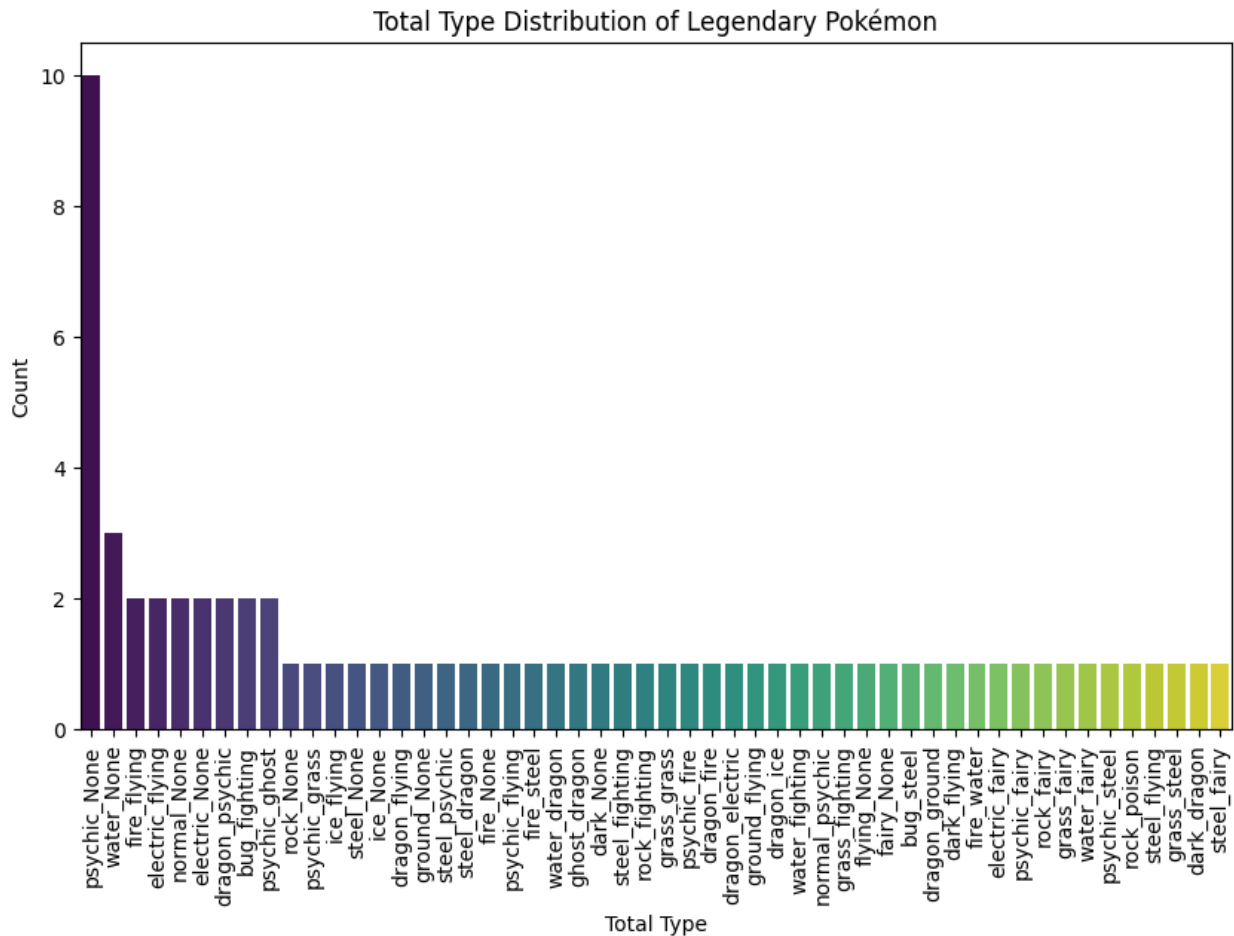


```
# Filter for legendary Pokémon
legendary_pokemon = df[df['is_legendary'] == 1]

# Count occurrences of each total type
total_type_counts = legendary_pokemon['type'].value_counts()

# Plot the distribution of total types
plt.figure(figsize=(10, 6))
sns.barplot(x=total_type_counts.index, y=total_type_counts.values,
palette="viridis")
plt.xlabel('Total Type')
plt.ylabel('Count')
plt.title('Total Type Distribution of Legendary Pokémon')
plt.xticks(rotation=90)

# Display the plot
plt.show()
```



From above plots, we can derive multiple conclusions:

- If a pokemon have primary type as "psychic" then it has a very high chance of being a legendary pokemon.
- If a pokemon have secondary type as "flying" then it has a very high chance of being a legendary pokemon.
- If a pokemon have primary and secondary type as follows then it has a good chance of being a legendary pokemon as well:
 - Dragon and Psychic type
 - Fire and Flying type
 - Electric and Flying type
 - Psychic and Ghost type
 - Bug and Fighting type

Classifying Legendary or not?

Selecting Features

```

featured_df = df[['attack', 'base_egg_steps', 'base_total', 'defense',
                  'experience_growth',
                  'height_m', 'hp',
                  'weight_kg', 'sp_attack', 'sp_defense', 'speed', 'tot_abilities',
                  'is_legendary']]
featured_df.head()

```

	attack	base_egg_steps	base_total	defense	experience_growth
height_m \					
0	49	5120	318	49	1059860
0.7					
1	62	5120	405	63	1059860
1.0					
2	100	5120	625	123	1059860
2.0					
3	52	5120	309	43	1059860
0.6					
4	64	5120	405	58	1059860
1.1					

	hp	weight_kg	sp_attack	sp_defense	speed	tot_abilities
is_legendary						
0	45	6.9	65	65	45	27
0						
1	60	13.0	80	80	60	27
0						
2	80	100.0	122	120	80	27
0						
3	39	8.5	60	50	65	24
0						
4	58	19.0	80	65	80	24
0						

Splitting the data into train & test sets

```

X = featured_df.drop("is_legendary", axis=1)    # predictors
y = featured_df["is_legendary"]                # target

# splitting the data
X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                    test_size=0.2, random_state=42)

print(f"Train set:\t{len(y_train)}")
print(f"Test set:\t{len(y_test)}")

Train set: 640
Test set: 161

```

Standardize features


```

# Standardize features
scaler = StandardScaler()

# Fit on training data
X_train = scaler.fit_transform(X_train)

# Apply transform to validation and test data
X_test = scaler.transform(X_test)

```

Model fitting and testing

```

# Initialize models
classifiers = {
    'Gradient Boosting': GradientBoostingClassifier(),
    'Random Forest': RandomForestClassifier(),
    'AdaBoost': AdaBoostClassifier(),
    'Support Vector Machine': SVC(),
    'Linear SVM': LinearSVC(),
    'K-Nearest Neighbors': KNeighborsClassifier(),
    'Gaussian Naive Bayes': GaussianNB(),
    'Decision Tree': DecisionTreeClassifier(),
    'Logistic Regression': LogisticRegression(),
    'Stochastic Gradient Descent': SGDClassifier(),
    'Neural Network': MLPClassifier(hidden_layer_sizes=(100, 100),
max_iter=1000),
    'XGBoost': XGBClassifier()
}

# Loop through each classifier
for name, clf in classifiers.items():
    # Fit the model on the training set
    clf.fit(X_train, y_train)

    # Predict on the test set for final evaluation
    y_test_pred = clf.predict(X_test)

    # Evaluate performance on test set
    test_accuracy = accuracy_score(y_test, y_test_pred)
    test_report = classification_report(y_test, y_test_pred)

    # Print results
    print(f"Algorithm: {name}")
    print("Test Set Results:")
    print(f"Accuracy: {test_accuracy:.2f}")
    print(test_report)
    print("="*55)

```

Algorithm: Gradient Boosting
Test Set Results:

Accuracy: 0.99

	precision	recall	f1-score	support
0	1.00	0.99	1.00	143
1	0.95	1.00	0.97	18
accuracy			0.99	161
macro avg	0.97	1.00	0.98	161
weighted avg	0.99	0.99	0.99	161

=====
Algorithm: Random Forest

Test Set Results:

Accuracy: 0.99

	precision	recall	f1-score	support
0	0.99	1.00	0.99	143
1	1.00	0.89	0.94	18
accuracy			0.99	161
macro avg	0.99	0.94	0.97	161
weighted avg	0.99	0.99	0.99	161

=====
Algorithm: AdaBoost

Test Set Results:

Accuracy: 0.99

	precision	recall	f1-score	support
0	1.00	0.99	1.00	143
1	0.95	1.00	0.97	18
accuracy			0.99	161
macro avg	0.97	1.00	0.98	161
weighted avg	0.99	0.99	0.99	161

=====
Algorithm: Support Vector Machine

Test Set Results:

Accuracy: 0.98

	precision	recall	f1-score	support
0	0.97	1.00	0.99	143
1	1.00	0.78	0.88	18
accuracy			0.98	161
macro avg	0.99	0.89	0.93	161
weighted avg	0.98	0.98	0.97	161

=====

Algorithm: Linear SVM

Test Set Results:

Accuracy: 0.98

	precision	recall	f1-score	support
0	0.98	1.00	0.99	143
1	1.00	0.83	0.91	18
accuracy			0.98	161
macro avg	0.99	0.92	0.95	161
weighted avg	0.98	0.98	0.98	161

=====
Algorithm: K-Nearest Neighbors

Test Set Results:

Accuracy: 0.98

	precision	recall	f1-score	support
0	0.98	1.00	0.99	143
1	1.00	0.83	0.91	18
accuracy			0.98	161
macro avg	0.99	0.92	0.95	161
weighted avg	0.98	0.98	0.98	161

=====
Algorithm: Gaussian Naive Bayes

Test Set Results:

Accuracy: 0.98

	precision	recall	f1-score	support
0	0.99	0.99	0.99	143
1	0.89	0.89	0.89	18
accuracy			0.98	161
macro avg	0.94	0.94	0.94	161
weighted avg	0.98	0.98	0.98	161

=====
Algorithm: Decision Tree

Test Set Results:

Accuracy: 0.98

	precision	recall	f1-score	support
0	0.99	0.99	0.99	143
1	0.89	0.94	0.92	18
accuracy			0.98	161
macro avg	0.94	0.97	0.95	161
weighted avg	0.98	0.98	0.98	161

=====
Algorithm: Logistic Regression

Test Set Results:

Accuracy: 0.98

	precision	recall	f1-score	support
0	0.98	1.00	0.99	143
1	1.00	0.83	0.91	18
accuracy			0.98	161
macro avg	0.99	0.92	0.95	161
weighted avg	0.98	0.98	0.98	161

=====
Algorithm: Stochastic Gradient Descent

Test Set Results:

Accuracy: 0.96

	precision	recall	f1-score	support
0	0.97	0.98	0.98	143
1	0.82	0.78	0.80	18
accuracy			0.96	161
macro avg	0.90	0.88	0.89	161
weighted avg	0.96	0.96	0.96	161

=====
Algorithm: Neural Network

Test Set Results:

Accuracy: 0.98

	precision	recall	f1-score	support
0	0.99	0.99	0.99	143
1	0.89	0.89	0.89	18
accuracy			0.98	161
macro avg	0.94	0.94	0.94	161
weighted avg	0.98	0.98	0.98	161

=====
Algorithm: XGBoost

Test Set Results:

Accuracy: 0.98

	precision	recall	f1-score	support
0	0.99	0.99	0.99	143
1	0.94	0.89	0.91	18
accuracy			0.98	161

macro avg	0.96	0.94	0.95	161
weighted avg	0.98	0.98	0.98	161

=====

Following is the comparison of models and their metrics such as accuracy, precision, recall, and F1-score.

Algorithm	Accuracy	Precision	Recall	F1-score	Class 0	Class 1	Class 0	Class 1	Class 0	Class 1
Gradient Boosting	0.99	1.00	0.95	0.99	1.00	1.00	0.97	Random Forest	0.99	0.99
1.00	0.89	0.99	0.94	AdaBoost	0.99	1.00	0.95	0.99	1.00	1.00
0.97	1.00	1.00	0.78	0.99	0.88	Linear SVM	0.98	0.98	1.00	1.00
0.83	0.99	0.91	Gaussian Naive Bayes	0.98	0.99	0.89	0.99	0.89	Decision Tree	0.98
0.99	0.89	0.99	0.89	0.99	0.89	0.99	0.92	Logistic Regression	0.98	0.98
1.00	1.00	0.83	0.99	0.91	Stochastic Gradient Descent	0.96	0.97	0.82	0.98	0.78
0.98	0.99	0.89	0.99	0.89	0.99	0.89	XGBoost	0.98	0.99	0.94
0.99	0.89	0.99	0.89	0.99	0.89	0.99	0.89	0.99	0.89	0.99

END of Notebook