# penguins.csv

## 1. Importação

In [1]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

## 2. Leitura do dataset

In [2]:
```
df = pd.read_csv('penguins.csv')
```

In [3]:
```
df
```

Out[3]:

| | species | island | culmen_length_mm | culmen_depth_mm | flipper_length_mm | body_mass_g | sex |
|---|---|---|---|---|---|---|---|
| **0** | 0.0 | 2.0 | 39.1 | 18.7 | 181.0 | 3750.0 | 1.0 |
| **1** | 0.0 | 2.0 | 39.5 | 17.4 | 186.0 | 3800.0 | 0.0 |
| **2** | 0.0 | 2.0 | 40.3 | 18.0 | 195.0 | 3250.0 | 0.0 |
| **3** | 0.0 | 2.0 | 36.7 | 19.3 | 193.0 | 3450.0 | 0.0 |
| **4** | 0.0 | 2.0 | 39.3 | 20.6 | 190.0 | 3650.0 | 1.0 |
| **...** | ... | ... | ... | ... | ... | ... | ... |
| **328** | 2.0 | 0.0 | 47.2 | 13.7 | 214.0 | 4925.0 | 0.0 |
| **329** | 2.0 | 0.0 | 46.8 | 14.3 | 215.0 | 4850.0 | 0.0 |
| **330** | 2.0 | 0.0 | 50.4 | 15.7 | 222.0 | 5750.0 | 1.0 |
| **331** | 2.0 | 0.0 | 45.2 | 14.8 | 212.0 | 5200.0 | 0.0 |
| **332** | 2.0 | 0.0 | 49.9 | 16.1 | 213.0 | 5400.0 | 1.0 |

333 rows × 7 columns

## 3. Definir um dataframe para cada especie

In [4]:
```
df['species'].unique()
```

Out[4]:
```
array([0., 1., 2.])
```

In [5]:
```
filt = (df['species'] == 'Adelie')
df_adelie = df.loc[filt]
```

In [6]:
```
filt = (df['species'] == 'Gentoo')
df_gentoo = df.loc[filt]
```

In [7]:
```
filt = (df['species'] == 'Chinstrap')
df_chinstrap = df.loc[filt]
```

## 4. Exploração

In [8]:
```
df.shape
```

Out[8]:
```
(333, 7)
```

In [9]:
```
df['species'].value_counts()
```

Out[9]:
```
0.0    146
2.0    119
1.0     68
Name: species, dtype: int64
```

In [10]:
```
df.isnull().sum(axis=0)
```

Out[10]:
```
species              0
island               0
culmen_length_mm     0
culmen_depth_mm      0
flipper_length_mm    0
body_mass_g          0
sex                  0
dtype: int64
```

In [11]:
```
df.drop(['species', 'island', 'sex'], axis=1).skew()
```

Out[11]:
```
culmen_length_mm     0.045340
culmen_depth_mm     -0.149720
flipper_length_mm    0.360148
body_mass_g          0.472246
dtype: float64
```

In [12]:
```
df.drop(['species', 'island', 'sex'], axis=1).kurt()
```

Out[12]:
```
culmen_length_mm    -0.883418
culmen_depth_mm     -0.891960
flipper_length_mm   -0.961241
body_mass_g         -0.733489
dtype: float64
```

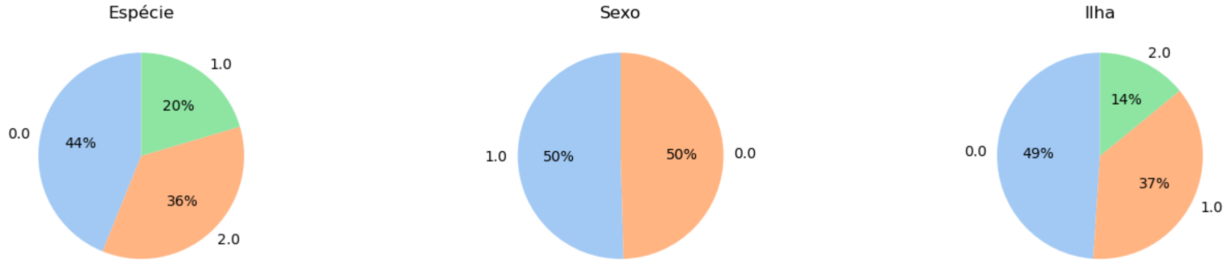
In [13]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 333 entries, 0 to 332
Data columns (total 7 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   species            333 non-null    float64
 1   island             333 non-null    float64
 2   culmen_length_mm   333 non-null    float64
 3   culmen_depth_mm    333 non-null    float64
 4   flipper_length_mm  333 non-null    float64
 5   body_mass_g        333 non-null    float64
 6   sex                333 non-null    float64
dtypes: float64(7)
memory usage: 18.3 KB
```

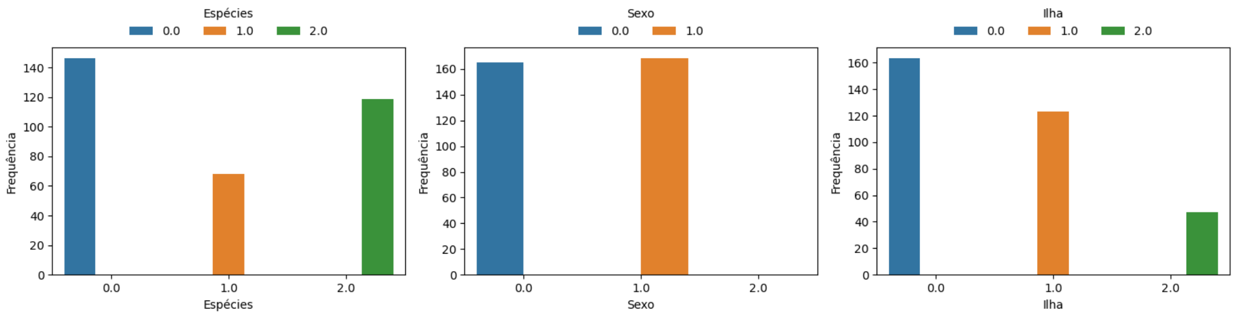
## 5. Análise

- Os pinguins Adelie são os que mais aparecem no conjunto de dados, seguidos pelas espécies Gentoo e Chinstrap.
- Os pinguins da amostra estão equilibrados em termos de sexo, existem exatamente 50% de dados masculinos e 50% de dados femininos.
- Metade dos pinguins está na Ilha Biscoe, uma minoria está na Ilha Torgersen e o restante está na Ilha dos Sonhos.

In [14]:
```
fig, ax = plt.subplots(figsize=(15, 3))

ax0 = plt.subplot2grid((1, 3),(0,0))
count = df['species'].value_counts()
labels = count.index
plt.pie(x=count, labels=labels, autopct='%.0f%%', startangle=90, colors=sns.color_palette("pastel"));
plt.title('Espécie')

ax1 = plt.subplot2grid((1, 3), (0, 1))
count = df['sex'].value_counts()
labels = count.index
plt.pie(x=count, labels=labels, autopct='%.0f%%', startangle=90, colors=sns.color_palette("pastel"));
plt.title('Sexo')

ax2 = plt.subplot2grid((1, 3), (0, 2))
count = df['island'].value_counts()
labels = count.index
plt.pie(x=count, labels=labels, autopct='%.0f%%', startangle=90, colors=sns.color_palette("pastel"));
plt.title('Ilha')

plt.tight_layout()
```




In [15]:
```
fig, ax = plt.subplots(nrows=1, ncols=3, figsize=(15, 4), sharex=True)

sns.countplot(data=df, x='species', hue='species', ax=ax[0])
ax[0].set_ylabel('Frequência')
ax[0].set_xlabel('Espécies')
sns.move_legend(ax[0], "lower center", bbox_to_anchor=(.5, 1), ncol=3, title='Espécies', frameon=False)

sns.countplot(data=df, x='sex', hue='sex', ax=ax[1])
ax[1].set_ylabel('Frequência')
ax[1].set_xlabel('Sexo')
sns.move_legend(ax[1], "lower center", bbox_to_anchor=(.5, 1), ncol=3, title='Sexo', frameon=False)

sns.countplot(data=df, x='island', hue='island', ax=ax[2])
ax[2].set_ylabel('Frequência')
ax[2].set_xlabel('Ilha')
sns.move_legend(ax[2], "lower center", bbox_to_anchor=(.5, 1), ncol=3, title='Ilha', frameon=False)

plt.tight_layout()
plt.show()
```




- Ao longo dos anos de amostragem, a quantidade de cada espécie tem se mantido relativamente estável, com pequenos aumentos e diminuições.
- A proporção de machos e fêmeas também tem se mantido estável, com um pequeno aumento em cada sexo a cada ano.
- Inicialmente, as ilhas Biscoe e Dream tinham quantidades semelhantes de pinguins, no entanto, em 2008, a ilha Biscoe apresentou um aumento considerável, enquanto a população em Dream diminuiu.

In [16]:
```
df.describe()
```

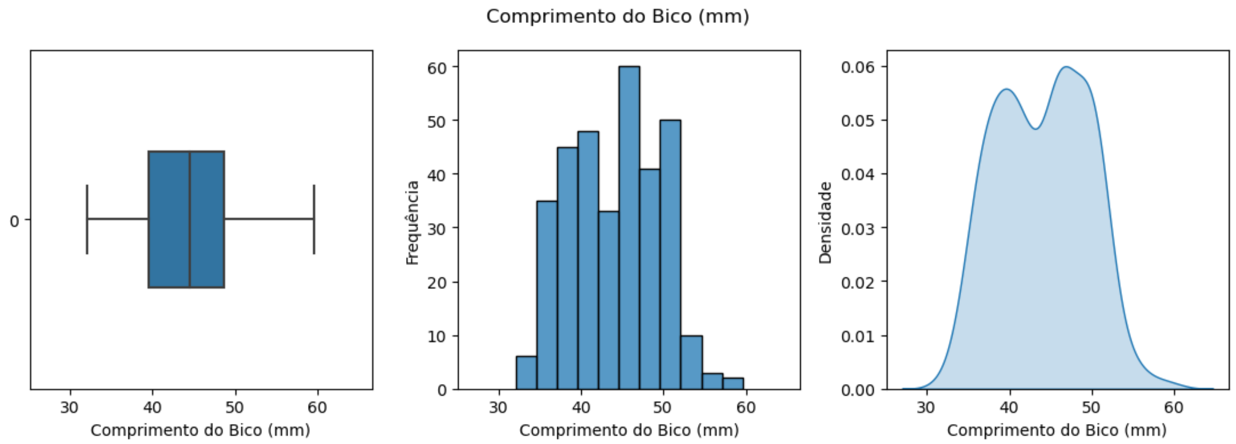
Out[16]:

| | species | island | culmen_length_mm | culmen_depth_mm | flipper_length_mm | body_mass_g | sex |
|---|---|---|---|---|---|---|---|
| **count** | 333.000000 | 333.000000 | 333.000000 | 333.000000 | 333.000000 | 333.000000 | 333.000000 |
| **mean** | 0.918919 | 0.651652 | 43.992793 | 17.164865 | 200.966967 | 4207.057057 | 0.504505 |
| **std** | 0.889718 | 0.714715 | 5.468668 | 1.969235 | 14.015765 | 805.215802 | 0.500732 |
| **min** | 0.000000 | 0.000000 | 32.100000 | 13.100000 | 172.000000 | 2700.000000 | 0.000000 |
| **25%** | 0.000000 | 0.000000 | 39.500000 | 15.600000 | 190.000000 | 3550.000000 | 0.000000 |
| **50%** | 1.000000 | 1.000000 | 44.500000 | 17.300000 | 197.000000 | 4050.000000 | 1.000000 |
| **75%** | 2.000000 | 1.000000 | 48.600000 | 18.700000 | 213.000000 | 4775.000000 | 1.000000 |
| **max** | 2.000000 | 2.000000 | 59.600000 | 21.500000 | 231.000000 | 6300.000000 | 1.000000 |

## Bico

- A mediana do comprimento do bico é de 44 mm.

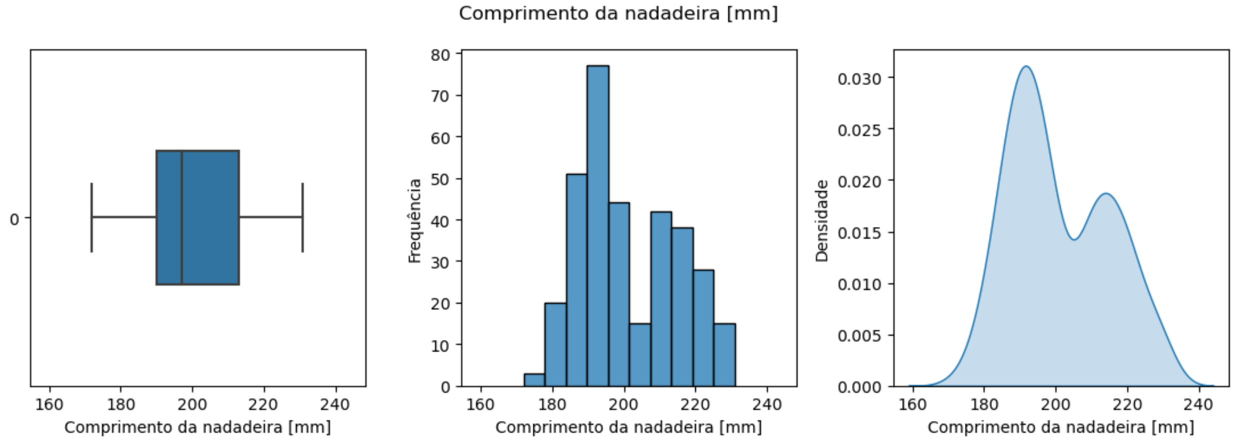
In [17]:
```python
var = 'culmen_length_mm'
var_title = 'Comprimento do Bico (mm)'

fig, ax = plt.subplots(nrows=1, ncols=3, figsize=(11, 4), sharex=True)

# Boxplot
sns.boxplot(data=df[var], ax=ax[0], orient='h', width=0.4)
ax[0].set_xlabel(var_title)

# Histograma
sns.histplot(data=df[var], ax=ax[1], kde=False)
ax[1].set_xlabel(var_title)
ax[1].set_ylabel('Frequência')

# Curva de densidade
sns.kdeplot(data=df[var], ax=ax[2], fill=True)
ax[2].set_xlabel(var_title)
ax[2].set_ylabel('Densidade')

fig.suptitle(var_title)

plt.tight_layout()
plt.show()
```




## Nadadeira

- A nadadeira possui uma mediana de 197 mm.

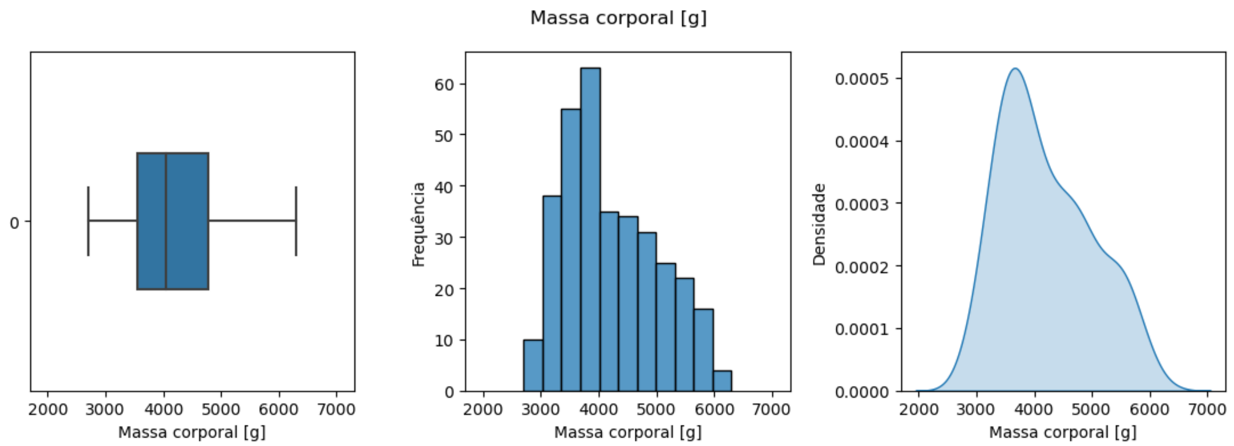
In [18]:
```python
var = 'flipper_length_mm'
var_title = 'Comprimento da nadadeira [mm]'
fig, ax = plt.subplots(nrows=1, ncols=3, figsize=(11, 4), sharex=True)

# Boxplot
sns.boxplot(data=df[var], ax=ax[0], orient='h', width=0.4)
ax[0].set_xlabel(var_title)

# Histograma
sns.histplot(data=df[var], ax=ax[1], kde=False)
ax[1].set_xlabel(var_title)
ax[1].set_ylabel('Frequência')

# Curva de densidade
sns.kdeplot(data=df[var], ax=ax[2], fill=True)
ax[2].set_xlabel(var_title)
ax[2].set_ylabel('Densidade')

fig.suptitle(var_title)

plt.tight_layout()
```




## Massa corporal

- Os pinguins têm uma massa corporal geralmente em torno de 4 kg.

In [19]:
```
var = 'body_mass_g'
var_title = 'Massa corporal [g]'
fig, ax = plt.subplots(nrows=1, ncols=3, figsize=(11, 4), sharex=True)

# Boxplot
sns.boxplot(data=df[var], ax=ax[0], orient='h', width=0.4)
ax[0].set_xlabel(var_title)

# Histograma
sns.histplot(data=df[var], ax=ax[1], kde=False)
ax[1].set_xlabel(var_title)
ax[1].set_ylabel('Frequência')

# Curva de densidade
sns.kdeplot(data=df[var], ax=ax[2], fill=True)
ax[2].set_xlabel(var_title)
ax[2].set_ylabel('Densidade')

fig.suptitle(var_title)

plt.tight_layout()
```

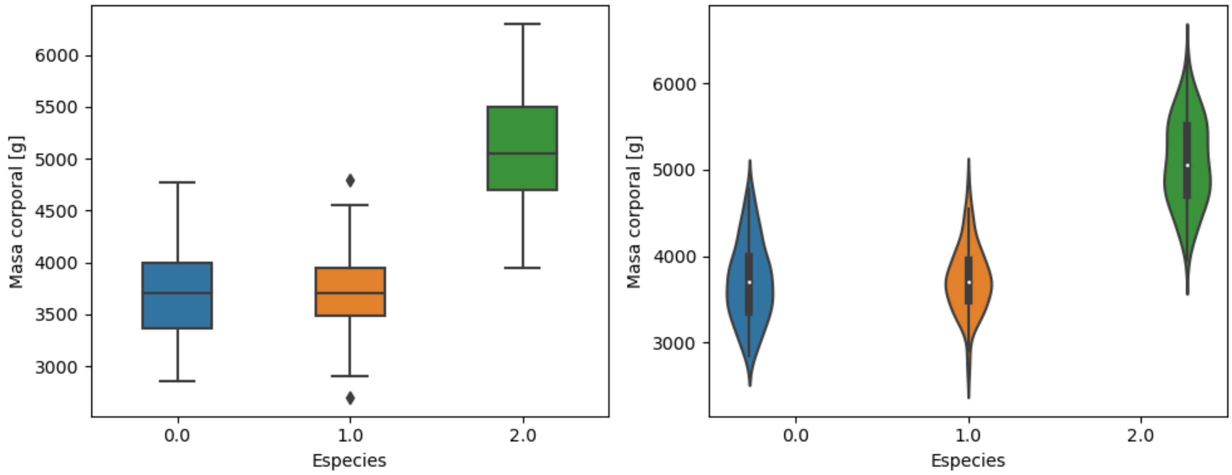



## Massa corporal comparado a cada espécies

- Gentoo pesa em torno de 5 kg.
- Adelie/Chinstrap pesam em torno de 3 e 4 kg.

In [20]:
```
var = 'body_mass_g'
var_title = 'Masa corporal [g]'
fig, ax = plt.subplots(nrows=1, ncols=2, figsize=(10, 4), sharex=True)

# Boxplot
sns.boxplot(data=df, x='species', y=var, ax=ax[0], width=.4)
ax[0].set_xlabel('Especies')
```

```
ax[0].set_ylabel(var_title)

# Diagrama de violino
sns.violinplot(data=df, x='species', y=var, ax=ax[1], hue='species')
ax[1].set_xlabel('Especies')
ax[1].set_ylabel(var_title)
ax[1].get_legend().remove()

plt.tight_layout()
```




## 6. Conclusão EDA

- Os pinguins da espécie Gentoo são os mais fáceis de distinguir:
  - Eles têm uma profundidade de pico menor.
  - Possuem uma maior comprimento de nadadeira e massa corporal em comparação com as outras espécies.
- Os pinguins da espécie Adelie geralmente têm um comprimento de bico menor.
- As espécies Adelie e Chinstrap geralmente possuem características mistas e às vezes são difíceis de separar.

## 7. DecisionTree / RandomForest

In [36]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

sns.set()
%matplotlib inline

from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn import metrics
from sklearn.metrics import classification_report, confusion_matrix
```

In [37]:
```
df = pd.read_csv('penguins.csv')
df.head()
```

Out[37]:

| | species | island | culmen_length_mm | culmen_depth_mm | flipper_length_mm | body_mass_g | sex |
|---|---|---|---|---|---|---|---|
| **0** | 0.0 | 2.0 | 39.1 | 18.7 | 181.0 | 3750.0 | 1.0 |
| **1** | 0.0 | 2.0 | 39.5 | 17.4 | 186.0 | 3800.0 | 0.0 |
| **2** | 0.0 | 2.0 | 40.3 | 18.0 | 195.0 | 3250.0 | 0.0 |
| **3** | 0.0 | 2.0 | 36.7 | 19.3 | 193.0 | 3450.0 | 0.0 |
| **4** | 0.0 | 2.0 | 39.3 | 20.6 | 190.0 | 3650.0 | 1.0 |

In [47]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 333 entries, 0 to 332
Data columns (total 7 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   species            333 non-null    float64
 1   island             333 non-null    float64
 2   culmen_length_mm   333 non-null    float64
 3   culmen_depth_mm    333 non-null    float64
 4   flipper_length_mm  333 non-null    float64
 5   body_mass_g        333 non-null    float64
 6   sex                333 non-null    float64
dtypes: float64(7)
memory usage: 20.8 KB
```

In [48]:
```
species_labels = ['species']
df = pd.get_dummies(df, columns=species_labels, drop_first=False)
```

In [49]:
```
island_labels = ['island']
df = pd.get_dummies(df, columns=island_labels, drop_first=False)
```

In [50]:
```
sex_labels = ['sex']
df = pd.get_dummies(df, columns=sex_labels, drop_first=False)
```

In [51]:
```
df
```

Out[51]:

| | culmen_length_mm | culmen_depth_mm | flipper_length_mm | body_mass_g | species_0.0 | species_1.0 | species_2.0 | island_0.0 | i |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 39.1 | 18.7 | 181.0 | 3750.0 | 1 | 0 | 0 | 0 | |
| **1** | 39.5 | 17.4 | 186.0 | 3800.0 | 1 | 0 | 0 | 0 | |
| **2** | 40.3 | 18.0 | 195.0 | 3250.0 | 1 | 0 | 0 | 0 | |
| **3** | 36.7 | 19.3 | 193.0 | 3450.0 | 1 | 0 | 0 | 0 | |
| **4** | 39.3 | 20.6 | 190.0 | 3650.0 | 1 | 0 | 0 | 0 | |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | |
| **328** | 47.2 | 13.7 | 214.0 | 4925.0 | 0 | 0 | 1 | 1 | |
| **329** | 46.8 | 14.3 | 215.0 | 4850.0 | 0 | 0 | 1 | 1 | |
| **330** | 50.4 | 15.7 | 222.0 | 5750.0 | 0 | 0 | 1 | 1 | |
| **331** | 45.2 | 14.8 | 212.0 | 5200.0 | 0 | 0 | 1 | 1 | |
| **332** | 49.9 | 16.1 | 213.0 | 5400.0 | 0 | 0 | 1 | 1 | |

333 rows × 12 columns

## Decision Tree

In [52]:
```
df.columns
```

Out[52]:
```
Index(['culmen_length_mm', 'culmen_depth_mm', 'flipper_length_mm',
       'body_mass_g', 'species_0.0', 'species_1.0', 'species_2.0',
       'island_0.0', 'island_1.0', 'island_2.0', 'sex_0.0', 'sex_1.0'],
      dtype='object')
```

In [53]:
```
x = df.drop('body_mass_g', axis=1)
y = df['body_mass_g']
```

In [64]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.3, random_state=101)
```

**Treinamento**

In [61]:
```
dtree = DecisionTreeClassifier()
```

In [63]:
```
dtree.fit(x_train, y_train)
```

Out[63]:
```
DecisionTreeClassifier()
```

**Prevendo os dados**

In [65]:
```
predictions = dtree.predict(x_test)
```

In [71]:
```
print(classification_report(y_test, predictions, zero_division=1))
```

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 2900.0 | 0.00 | 0.00 | 0.00 | 1 |
| 2925.0 | 1.00 | 0.00 | 0.00 | 1 |
| 3000.0 | 1.00 | 0.00 | 0.00 | 2 |
| 3050.0 | 0.00 | 0.00 | 0.00 | 1 |
| 3100.0 | 0.00 | 1.00 | 0.00 | 0 |
| 3150.0 | 0.00 | 1.00 | 0.00 | 0 |
| 3175.0 | 1.00 | 0.00 | 0.00 | 1 |
| 3200.0 | 1.00 | 0.00 | 0.00 | 2 |
| 3250.0 | 0.00 | 0.00 | 0.00 | 2 |
| 3275.0 | 0.00 | 1.00 | 0.00 | 0 |
| 3300.0 | 0.00 | 0.00 | 0.00 | 2 |
| 3325.0 | 1.00 | 0.00 | 0.00 | 3 |
| 3350.0 | 0.00 | 0.00 | 0.00 | 2 |
| 3400.0 | 0.00 | 0.00 | 0.00 | 2 |
| 3425.0 | 1.00 | 0.00 | 0.00 | 2 |
| 3450.0 | 0.00 | 0.00 | 0.00 | 1 |
| 3475.0 | 1.00 | 0.00 | 0.00 | 1 |
| 3500.0 | 0.20 | 0.50 | 0.29 | 2 |
| 3525.0 | 0.00 | 1.00 | 0.00 | 0 |
| 3550.0 | 0.00 | 0.00 | 0.00 | 2 |
| 3575.0 | 0.00 | 1.00 | 0.00 | 0 |
| 3600.0 | 0.00 | 0.00 | 0.00 | 4 |
| 3650.0 | 0.00 | 0.00 | 0.00 | 2 |
| 3675.0 | 0.50 | 1.00 | 0.67 | 1 |
| 3700.0 | 0.00 | 0.00 | 0.00 | 4 |
| 3725.0 | 1.00 | 0.00 | 0.00 | 1 |
| 3750.0 | 0.00 | 0.00 | 0.00 | 1 |
| 3775.0 | 1.00 | 0.00 | 0.00 | 3 |
| 3800.0 | 0.00 | 0.00 | 0.00 | 3 |
| 3825.0 | 1.00 | 0.00 | 0.00 | 1 |
| 3875.0 | 1.00 | 0.00 | 0.00 | 1 |
| 3900.0 | 0.00 | 0.00 | 0.00 | 1 |
| 3950.0 | 0.00 | 0.00 | 0.00 | 3 |
| 3975.0 | 0.00 | 1.00 | 0.00 | 0 |
| 4000.0 | 0.00 | 0.00 | 0.00 | 1 |
| 4075.0 | 0.00 | 1.00 | 0.00 | 0 |
| 4100.0 | 1.00 | 0.00 | 0.00 | 2 |
| 4150.0 | 0.00 | 0.00 | 0.00 | 3 |
| 4200.0 | 0.00 | 0.00 | 0.00 | 1 |
| 4250.0 | 0.00 | 0.00 | 0.00 | 1 |
| 4300.0 | 0.50 | 0.25 | 0.33 | 4 |
| 4350.0 | 1.00 | 0.00 | 0.00 | 1 |
| 4400.0 | 0.20 | 0.25 | 0.22 | 4 |
| 4450.0 | 0.00 | 1.00 | 0.00 | 0 |
| 4500.0 | 1.00 | 0.00 | 0.00 | 1 |
| 4575.0 | 0.00 | 1.00 | 0.00 | 0 |
| 4600.0 | 0.00 | 0.00 | 0.00 | 1 |
| 4625.0 | 1.00 | 0.00 | 0.00 | 2 |
| 4650.0 | 0.00 | 0.00 | 0.00 | 2 |
| 4675.0 | 0.00 | 1.00 | 0.00 | 0 |
| 4700.0 | 0.00 | 0.00 | 0.00 | 1 |
| 4725.0 | 0.00 | 0.00 | 0.00 | 1 |
| 4750.0 | 0.00 | 0.00 | 0.00 | 1 |
| 4775.0 | 0.00 | 1.00 | 0.00 | 0 |
| 4800.0 | 1.00 | 0.00 | 0.00 | 2 |
| 4850.0 | 1.00 | 0.00 | 0.00 | 2 |
| 4875.0 | 1.00 | 0.00 | 0.00 | 1 |
| 4950.0 | 0.00 | 1.00 | 0.00 | 0 |
| 5000.0 | 0.00 | 1.00 | 0.00 | 0 |
| 5050.0 | 0.00 | 1.00 | 0.00 | 0 |
| 5100.0 | 0.00 | 1.00 | 0.00 | 0 |
| 5150.0 | 0.00 | 1.00 | 0.00 | 0 |
| 5200.0 | 1.00 | 0.00 | 0.00 | 3 |
| 5250.0 | 1.00 | 0.00 | 0.00 | 1 |
| 5300.0 | 1.00 | 0.00 | 0.00 | 2 |
| 5350.0 | 1.00 | 0.00 | 0.00 | 2 |
| 5400.0 | 0.00 | 0.00 | 0.00 | 1 |
| 5500.0 | 0.00 | 0.00 | 0.00 | 1 |
| 5550.0 | 0.00 | 0.00 | 0.00 | 2 |
| 5600.0 | 1.00 | 0.00 | 0.00 | 1 |
| 5650.0 | 0.00 | 1.00 | 0.00 | 0 |
| 5750.0 | 0.00 | 1.00 | 0.00 | 0 |
| 5800.0 | 1.00 | 0.00 | 0.00 | 2 |
| 5850.0 | 0.00 | 1.00 | 0.00 | 0 |
| 5950.0 | 1.00 | 0.00 | 0.00 | 1 |
| 6300.0 | 1.00 | 0.00 | 0.00 | 1 |
| accuracy | | | 0.04 | 100 |

```
   macro avg       0.36      0.28      0.02       100
weighted avg       0.46      0.04      0.03       100
```

In [72]:
```
print(confusion_matrix(y_test, predictions))
```

```
[[0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 ...
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]]
```

# Random Forest

#### Treinamento

In [73]:
```
rfc = RandomForestClassifier(n_estimators=200)
```

In [74]:
```
rfc.fit(x_train, y_train)
```

Out[74]:
```
RandomForestClassifier(n_estimators=200)
```

#### Prevendo os dados

In [75]:
```
predictions = rfc.predict(x_test)
```

In [77]:
```
print(classification_report(y_test, predictions, zero_division=1))
```

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 2700.0 | 0.00 | 1.00 | 0.00 | 0 |
| 2900.0 | 0.00 | 0.00 | 0.00 | 1 |
| 2925.0 | 1.00 | 0.00 | 0.00 | 1 |
| 3000.0 | 1.00 | 0.00 | 0.00 | 2 |
| 3050.0 | 0.00 | 0.00 | 0.00 | 1 |
| 3150.0 | 0.00 | 1.00 | 0.00 | 0 |
| 3175.0 | 0.00 | 0.00 | 0.00 | 1 |
| 3200.0 | 0.00 | 0.00 | 0.00 | 2 |
| 3250.0 | 0.00 | 0.00 | 0.00 | 2 |
| 3275.0 | 0.00 | 1.00 | 0.00 | 0 |
| 3300.0 | 0.00 | 0.00 | 0.00 | 2 |
| 3325.0 | 0.00 | 0.00 | 0.00 | 3 |
| 3350.0 | 0.00 | 0.00 | 0.00 | 2 |
| 3400.0 | 0.00 | 0.00 | 0.00 | 2 |
| 3425.0 | 1.00 | 0.00 | 0.00 | 2 |
| 3450.0 | 0.00 | 0.00 | 0.00 | 1 |
| 3475.0 | 1.00 | 0.00 | 0.00 | 1 |
| 3500.0 | 0.17 | 0.50 | 0.25 | 2 |
| 3525.0 | 0.00 | 1.00 | 0.00 | 0 |
| 3550.0 | 0.00 | 0.00 | 0.00 | 2 |
| 3600.0 | 0.00 | 0.00 | 0.00 | 4 |
| 3650.0 | 0.00 | 0.00 | 0.00 | 2 |
| 3675.0 | 1.00 | 0.00 | 0.00 | 1 |
| 3700.0 | 0.00 | 0.00 | 0.00 | 4 |
| 3725.0 | 0.00 | 0.00 | 0.00 | 1 |
| 3750.0 | 0.00 | 0.00 | 0.00 | 1 |
| 3775.0 | 1.00 | 0.00 | 0.00 | 3 |
| 3800.0 | 1.00 | 0.00 | 0.00 | 3 |
| 3825.0 | 1.00 | 0.00 | 0.00 | 1 |
| 3875.0 | 1.00 | 0.00 | 0.00 | 1 |
| 3900.0 | 0.00 | 0.00 | 0.00 | 1 |
| 3950.0 | 0.00 | 0.00 | 0.00 | 3 |
| 4000.0 | 0.00 | 0.00 | 0.00 | 1 |
| 4050.0 | 0.00 | 1.00 | 0.00 | 0 |
| 4100.0 | 0.00 | 0.00 | 0.00 | 2 |
| 4150.0 | 1.00 | 0.00 | 0.00 | 3 |
| 4200.0 | 0.00 | 0.00 | 0.00 | 1 |
| 4250.0 | 1.00 | 0.00 | 0.00 | 1 |
| 4300.0 | 1.00 | 0.25 | 0.40 | 4 |
| 4350.0 | 0.00 | 0.00 | 0.00 | 1 |
| 4400.0 | 1.00 | 0.00 | 0.00 | 4 |
| 4450.0 | 0.00 | 1.00 | 0.00 | 0 |
| 4500.0 | 1.00 | 0.00 | 0.00 | 1 |
| 4550.0 | 0.00 | 1.00 | 0.00 | 0 |
| 4600.0 | 0.00 | 0.00 | 0.00 | 1 |
| 4625.0 | 1.00 | 0.00 | 0.00 | 2 |
| 4650.0 | 1.00 | 0.00 | 0.00 | 2 |
| 4675.0 | 0.00 | 1.00 | 0.00 | 0 |
| 4700.0 | 0.00 | 0.00 | 0.00 | 1 |
| 4725.0 | 0.00 | 0.00 | 0.00 | 1 |
| 4750.0 | 0.50 | 1.00 | 0.67 | 1 |
| 4800.0 | 0.00 | 0.00 | 0.00 | 2 |
| 4850.0 | 1.00 | 0.00 | 0.00 | 2 |
| 4875.0 | 1.00 | 0.00 | 0.00 | 1 |
| 4925.0 | 0.00 | 1.00 | 0.00 | 0 |
| 4950.0 | 0.00 | 1.00 | 0.00 | 0 |
| 5000.0 | 0.00 | 1.00 | 0.00 | 0 |
| 5050.0 | 0.00 | 1.00 | 0.00 | 0 |
| 5100.0 | 0.00 | 1.00 | 0.00 | 0 |
| 5150.0 | 0.00 | 1.00 | 0.00 | 0 |
| 5200.0 | 1.00 | 0.00 | 0.00 | 3 |
| 5250.0 | 1.00 | 0.00 | 0.00 | 1 |
| 5300.0 | 1.00 | 0.00 | 0.00 | 2 |
| 5350.0 | 1.00 | 0.00 | 0.00 | 2 |
| 5400.0 | 0.00 | 0.00 | 0.00 | 1 |
| 5500.0 | 0.00 | 0.00 | 0.00 | 1 |
| 5550.0 | 0.33 | 0.50 | 0.40 | 2 |
| 5600.0 | 1.00 | 0.00 | 0.00 | 1 |
| 5700.0 | 0.00 | 1.00 | 0.00 | 0 |
| 5800.0 | 1.00 | 0.00 | 0.00 | 2 |
| 5950.0 | 1.00 | 0.00 | 0.00 | 1 |
| 6000.0 | 0.00 | 1.00 | 0.00 | 0 |
| 6300.0 | 1.00 | 0.00 | 0.00 | 1 |
| accuracy | | | 0.04 | 100 |
| macro avg | 0.37 | 0.25 | 0.02 | 100 |
| weighted avg | 0.49 | 0.04 | 0.04 | 100 |

In [78]:
```
print(confusion_matrix(y_test, predictions))
```

```
[[0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 ...
 [0 0 0 ... 0 1 0]
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]]
```

In [ ]: