Setup Data

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

url = ("https://archive.ics.uci.edu/ml/machine-learning-databases/abalone/abalone.data")
abalone = pd.read_csv(url, header=None)
abalone.columns = ["Sex","Length","Diameter","Height","Whole weight","Shucked weight","Viscera weight","Shell weight","Rings",]
abalone.head(3)
```

	Sex	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings
0	M	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.15	15
1	M	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.07	7
2	F	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.21	9

```
abalone = abalone.drop('Sex', axis=1)
abalone.head(3)
```

	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings
0	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.15	15
1	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.07	7
2	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.21	9

Analisis Exploratorio

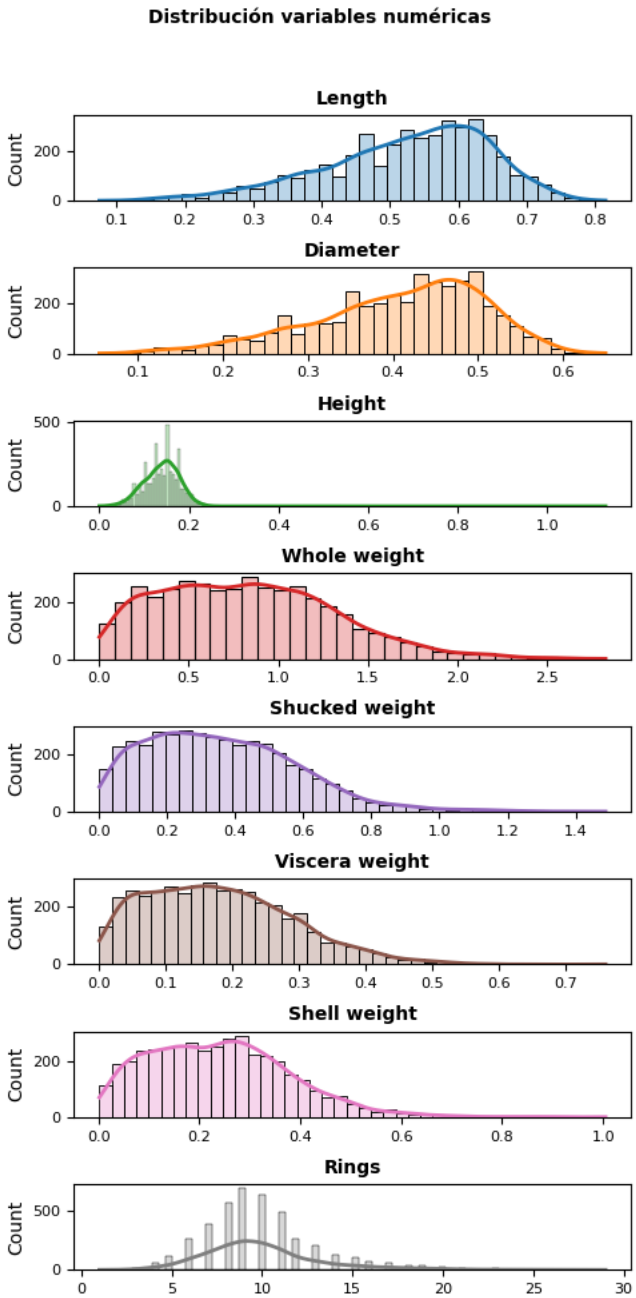
```
abalone.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4177 entries, 0 to 4176
Data columns (total 8 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Length          4177 non-null   float64
 1   Diameter        4177 non-null   float64
 2   Height          4177 non-null   float64
 3   Whole weight    4177 non-null   float64
 4   Shucked weight  4177 non-null   float64
 5   Viscera weight  4177 non-null   float64
 6   Shell weight    4177 non-null   float64
 7   Rings           4177 non-null   int64
dtypes: float64(7), int64(1)
memory usage: 261.2 KB
```

```
fig, axes = plt.subplots(nrows=8, ncols=1, figsize=(5,10))
axes = axes.flat
data = abalone.select_dtypes(include=['float64', 'int']).columns

for i, colum in enumerate(data):
    sns.histplot(
        data    = abalone,
        x       = colum,
        stat    = "count",
        kde     = True,
        color   = (list(plt.rcParams['axes.prop_cycle'])*2)[i]["color"],
        line_kws= {'linewidth': 2},
        alpha   = 0.3,
        ax      = axes[i]
    )
    axes[i].set_title(colum, fontsize = 10, fontweight = "bold")
    axes[i].tick_params(labelsize = 8)
    axes[i].set_xlabel("")
```

```
fig.tight_layout()
plt.subplots_adjust(top = 0.9)
fig.suptitle('Distribución variables numéricas', fontsize = 10, fontweight = "bold");
```




```
abalone.describe()
```

	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Sh wei
count	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.000
mean	0.523992	0.407881	0.139516	0.828742	0.359367	0.180594	0.238
std	0.120093	0.099240	0.041827	0.490389	0.221963	0.109614	0.139
min	0.075000	0.055000	0.000000	0.002000	0.001000	0.000500	0.001
25%	0.450000	0.350000	0.115000	0.441500	0.186000	0.093500	0.130
50%	0.545000	0.425000	0.140000	0.799500	0.336000	0.171000	0.234
75%	0.615000	0.480000	0.165000	1.153000	0.502000	0.253000	0.329
max	0.815000	0.650000	1.130000	2.825500	1.488000	0.760000	1.005

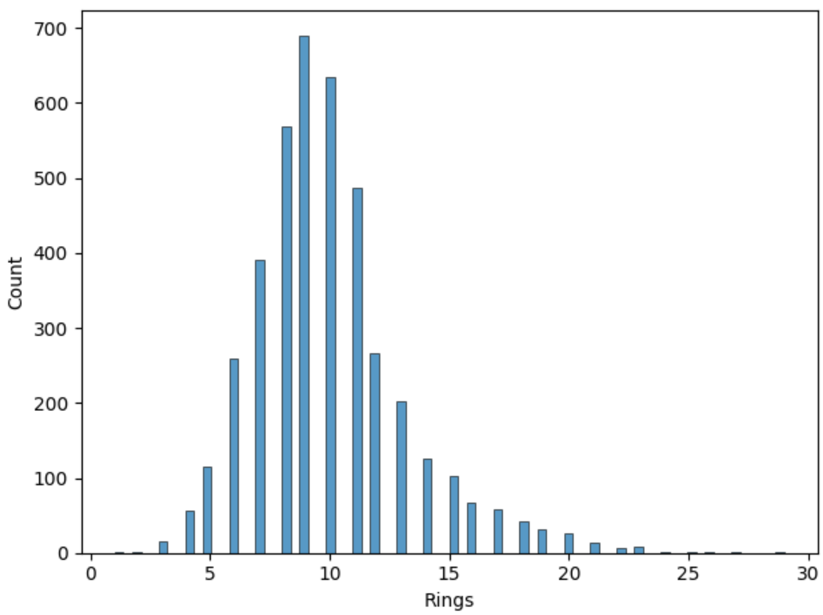
Al observar la distribucion de las variables, se logra identificar una tendencia a ser una distribucion normal en las variables de Length, Diameter, Height y Rings. Mientras que los pesos ("Weight's") distrubuyen normal positivamente.

Sin embargo, nuestra variable de interes "Rings", tiene una distribucion normal estandar mas marcada, para esto la observaremos mas detalladamente.

Distribucion Variable Interes "Rings"

```
sns.histplot(data=abalone['Rings'])

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



Comparando los datos obtenidos con el metodo Describe(), se observa claramente que la media esta aproximadamente en 10 rings, y que tambien existe una asimetria positiva en los valores de rings mas elevados.

Correlacion de las variables

```
correlation = abalone.corr()
correlation['Rings']
```

```
Length            0.556720
Diameter          0.574660
Height            0.557467
Whole weight      0.540390
Shucked weight    0.420884
Viscera weight    0.503819
Shell weight      0.627574
Rings             1.000000
Name: Rings, dtype: float64
```

En cuanto a la correlacion de las variables con respuesto a la Variable Respuesta "Rings", se observa una correlacion moderada en la mayoria de las variables que sobrepasan un valor de 0.5. Exceptuando la variable Shucked Weight, que podria ser una candidata a ser descartada, debido a que es la variable con mas baja correlacion respecto a las demas.

Definiendo Distancias

```
X = abalone.drop('Rings', axis=1)
X = X.values
Y = abalone['Rings']
Y = Y.values

#AbulonMeanValues
abulonPoint = np.array([0.523992,0.407881,0.139516,0.828742,0.359367,0.180594,0.238831])


distances = np.linalg.norm(X - abulonPoint, axis=1)
display(distances)
```

```
array([0.37424342, 0.72837115, 0.1901846 , ..., 0.42305067, 0.35507533,
       1.32692616])
```

Para observar algunos datos vecinos con algun punto de interes, se definio los valores promedios de todas las variables para observar que datos estan cercanos al promedio.

Determinando vecinos cercanos

```
k = 3

vecinosCercanos = distances.argsort()[:k]
display(vecinosCercanos)
```

```
array([2892, 3833, 1599], dtype=int64)
```

Por ultimo, los datos vecinos que son cercanos a el punto definido anteriormente fueron los siguientes datos:

```
display(abalone.iloc[2892])
display(abalone.iloc[3833])
display(abalone.iloc[1599])
```

```
Length             0.5300
Diameter           0.4050
Height             0.1500
Whole weight       0.8315
Shucked weight     0.3520
Viscera weight     0.1870
Shell weight       0.2525
Rings             10.0000
Name: 2892, dtype: float64
Length             0.5350
Diameter           0.4100
Height             0.1500
Whole weight       0.8105
Shucked weight     0.3450
Viscera weight     0.1870
Shell weight       0.2400
Rings             11.0000
Name: 3833, dtype: float64
Length             0.5300
Diameter           0.4200
Height             0.1300
Whole weight       0.8365
Shucked weight     0.3745
Viscera weight     0.1670
Shell weight       0.2490
Rings             11.0000
Name: 1599, dtype: float64
```