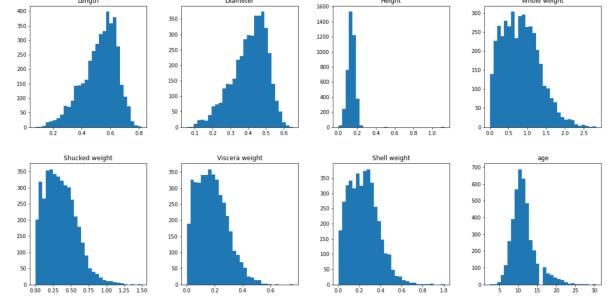
#### **IMPORTING LIBRARIES**

```
In []:
    import pandas as pd
    import numpy as np
    from matplotlib import pyplot as plt
    import seaborn as sns
    from sklearn.linear_model import LinearRegression
```

#### 2. Load the dataset into the Google Colab

```
In []: df=pd.read_csv("/content/abalone.csv")
In []: df['age'] = df['Rings']+1.5
    df = df.drop('Rings', axis = 1)
```

#### 3. UNIVARIATE ANALYSIS

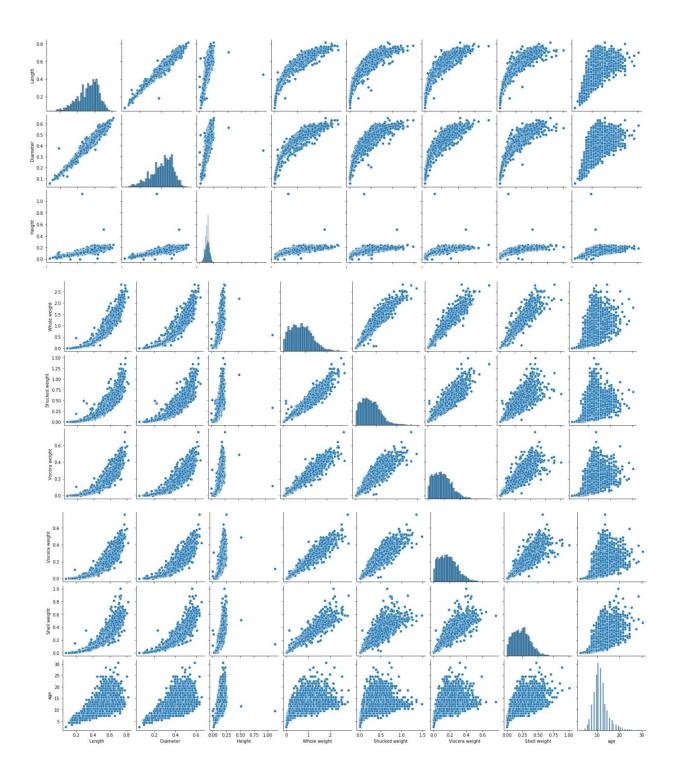


t[]:		Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	age
	Sex								
	- 1	0.427746	0.326494	0.107996	0.431363	0.191035	0.092010	0.128182	9.390462
	М	0.561391	0.439287	0.151381	0.991459	0.432946	0.215545	0.281969	12.205497
	F	0.579093	0.454732	0.158011	1.046532	0.446188	0.230689	0.302010	12.629304

#### 3. BIVARIATE ANALYSIS & MULTIVARIATE ANALYSIS

```
In [ ]:
    numerical_features = df.select_dtypes(include = [np.number]).columns
    sns.pairplot(df[numerical_features])
```

Out[ ]: Seaborn.axisgrid.PairGrid at 0x7fc8fde17fd0>



### 4. Descriptive statistics

# In [ ]: df.describe()

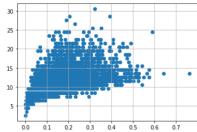
t[ ]:		Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	age
	count	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000
	mean	0.523992	0.407881	0.139516	0.828742	0.359367	0.180594	0.238831	11.433684
	std	0.120093	0.099240	0.041827	0.490389	0.221963	0.109614	0.139203	3.224169
	min	0.075000	0.055000	0.000000	0.002000	0.001000	0.000500	0.001500	2.500000
	25%	0.450000	0.350000	0.115000	0.441500	0.186000	0.093500	0.130000	9.500000
	50%	0.545000	0.425000	0.140000	0.799500	0.336000	0.171000	0.234000	10.500000
	75%	0.615000	0.480000	0.165000	1.153000	0.502000	0.253000	0.329000	12.500000
	max	0.815000	0.650000	1.130000	2.825500	1.488000	0.760000	1.005000	30.500000

### 5. Check for Missing Values

```
In []: df.isnull().sum()

Out[]: Sex 0
Length 0
Diameter 0
Height 0
Whole weight 0
Shucked weight 0
Viscera weight 0
Shell weight 0
age 0
dtype: int64
```

# 6. OUTLIER HANDLING



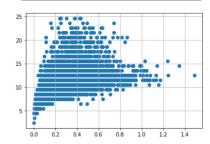
```
In []:
    # outliers removal
    df.drop(df[(df['Viscera weight']> 0.5) & (df['age'] < 20)].index, inplace=True)
    df.drop(df[(df['Viscera weight']< 0.5) & (df['age'] > 25)].index, inplace=True)
```

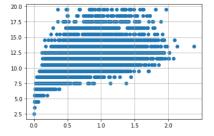
```
In []:
    var = 'Shell weight'
    plt.scatter(x = df[var], y = df['age'],)
    plt.grid(True)
    #Outliers removal
    df.drop(df[(df['Shell weight']> 0.6) & (df['age'] < 25)].index, inplace=True)
    df.drop(df[(df['Shell weight']<0.8) & (df['age'] > 25)].index, inplace=True)
```

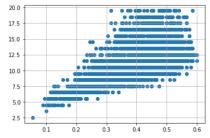
```
25 20 20 15 10 00 02 04 06 08 10
```

```
In []:
    var = 'Shucked weight'
    plt.scatter(x = df[var], y = df['age'],)
    plt.grid(True)

#Outlier removal
    df.drop(df[(df['Shucked weight']>= 1) & (df['age'] < 20)].index, inplace=True)
    df.drop(df[(df['Shucked weight']<1) & (df['age'] > 20)].index, inplace=True)
```

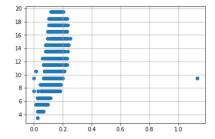


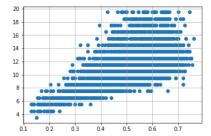




```
In []:
    var = 'Height'
    plt.scatter(x = df[var], y = df['age'])
    plt.grid(True)
    df.drop(df[(df['Height'] > 0.4) &
        (df['age'] < 15)].index, inplace = True)

    df.drop(df[(df['Height'] \cdot 0.4) & (
        df['age'] > 25)].index, inplace = True)
```





#### 7. Categorical columns

```
In [1]: numerical_features = df.select_dtypes(include = [np.number]).columns

In [19]: numerical_features

Out[19]: Index(['Length', 'Diameter', 'Height', 'Whole weight', 'Shucked weight', 'Viscera weight', 'Shell weight', 'Sex_F', 'Sex_I', 'Sex_M'],

In [20]: categorical_features

Out[20]: Index([], dtype='object')
```

# **ENCODING**

#### 8. Split the dependent and independent variables

```
In [22]: x=df.iloc[:,:5] x
```

vet[22]:         Length         Diameter         Height         Whole weight         Shucked weight           0         0.455         0.365         0.095         0.5140         0.2245           1         0.350         0.0265         0.090         0.2255         0.0995           2         0.530         0.420         0.135         0.6770         0.2565           3         0.440         0.365         0.125         0.5160         0.2155           4         0.330         0.255         0.080         0.2050         0.0895                    4172         0.565         0.450         0.165         0.8870         0.3700         4390           4173         0.590         0.440         0.135         0.9660         0.4390           4174         0.600         0.475         0.205         1.1760         0.5255           4175         0.625         0.485         0.150         1.0945         0.5310           4176         0.710         0.555         0.195         1.9485         0.9455							
1       0.350       0.265       0.090       0.2255       0.0995         2       0.530       0.420       0.135       0.6770       0.2565         3       0.440       0.365       0.125       0.5160       0.2155         4       0.330       0.255       0.080       0.2050       0.0895                  4172       0.565       0.450       0.165       0.8870       0.3700         4173       0.590       0.440       0.135       0.9660       0.4390         4174       0.600       0.475       0.205       1.1760       0.5255         4175       0.625       0.485       0.150       1.0945       0.5310	ut[22]:		Length	Diameter	Height	Whole weight	Shucked weight
2       0.530       0.420       0.135       0.6770       0.2565         3       0.440       0.365       0.125       0.5160       0.2155         4       0.330       0.255       0.080       0.2050       0.0895                 4172       0.565       0.450       0.165       0.8870       0.3700         4173       0.590       0.440       0.135       0.9660       0.4390         4174       0.600       0.475       0.205       1.1760       0.5255         4175       0.625       0.485       0.150       1.0945       0.5310		0	0.455	0.365	0.095	0.5140	0.2245
3     0.440     0.365     0.125     0.5160     0.2155       4     0.330     0.255     0.080     0.2050     0.0895                4172     0.565     0.450     0.165     0.8870     0.3700       4173     0.590     0.440     0.135     0.9660     0.4390       4174     0.600     0.475     0.205     1.1760     0.5255       4175     0.625     0.485     0.150     1.0945     0.5310		1	0.350	0.265	0.090	0.2255	0.0995
4       0.330       0.255       0.080       0.2050       0.0895                   4172       0.565       0.450       0.165       0.8870       0.3700         4173       0.590       0.440       0.135       0.9660       0.4390         4174       0.600       0.475       0.205       1.1760       0.5255         4175       0.625       0.485       0.150       1.0945       0.5310		2	0.530	0.420	0.135	0.6770	0.2565
4172     0.565     0.450     0.165     0.8870     0.3700       4173     0.590     0.440     0.135     0.9660     0.4390       4174     0.600     0.475     0.205     1.1760     0.5255       4175     0.625     0.485     0.150     1.0945     0.5310		3	0.440	0.365	0.125	0.5160	0.2155
4172         0.565         0.450         0.165         0.8870         0.3700           4173         0.590         0.440         0.135         0.9660         0.4390           4174         0.600         0.475         0.205         1.1760         0.5255           4175         0.625         0.485         0.150         1.0945         0.5310		4	0.330	0.255	0.080	0.2050	0.0895
4173         0.590         0.440         0.135         0.9660         0.4390           4174         0.600         0.475         0.205         1.1760         0.5255           4175         0.625         0.485         0.150         1.0945         0.5310							
4174         0.600         0.475         0.205         1.1760         0.5255           4175         0.625         0.485         0.150         1.0945         0.5310		4172	0.565	0.450	0.165	0.8870	0.3700
<b>4175</b> 0.625 0.485 0.150 1.0945 0.5310		4173	0.590	0.440	0.135	0.9660	0.4390
		4174	0.600	0.475	0.205	1.1760	0.5255
<b>4176</b> 0.710 0.555 0.195 1.9485 0.9455		4175	0.625	0.485	0.150	1.0945	0.5310
		4176	0.710	0.555	0.195	1.9485	0.9455

3995 rows × 5 columns

```
In [23]: y=df.iloc[:,5:] y
```

Out[23]:		Viscera weight	Shell weight	age	Sex_F	Sex_I	Sex_M
	0	0.1010	0.1500	16.5	0	0	1
	1	0.0485	0.0700	8.5	0	0	1
	2	0.1415	0.2100	10.5	1	0	0
	3	0.1140	0.1550	11.5	0	0	1
	4	0.0395	0.0550	8.5	0	1	0
	4172	0.2390	0.2490	12.5	1	0	0
	4173	0.2145	0.2605	11.5	0	0	1
	4174	0.2875	0.3080	10.5	0	0	1
	4175	0.2610	0.2960	11.5	1	0	0
	4176	0.3765	0.4950	13.5	0	0	1

3995 rows × 6 columns

### 9. Feature Scaling

In [26]:	<pre>from sklearn.preprocessing import StandardScaler ss=StandardScaler() x_train=ss.fit_transform(x_train)</pre>
In [ ]:	mlrpred=mlr.predict(x_test[0:9])
In [ ]:	mlrpred

# 10. Train , Test , Split

In [25]:
 from sklearn.model\_selection import train\_test\_split
 x\_train,x\_test,y\_train,y\_test=train\_test\_split(x,y,test\_size=0.2)

# 11. Model building

In [ ]: from sklearn.linear\_model import LinearRegression
 mlr=LinearRegression()
 mlr.fit(x\_train,y\_train)

#### 12 & 13. Train and Test the model

```
In []: x_test[0:5]

In []: y_test[0:5]
```

### 14. Measure the performance using metrics

In [ ]:
 from sklearn.metrics import r2\_score
 r2\_score(mlr.predict(x\_test),y\_test)