In [1]:	Import libraries
	<pre>import pandas as pd # data manipulation import numpy as np # linear algebra import matplotlib.pyplot as plt # plots import seaborn as sns # plots</pre>
In [2]:	<pre>import warnings # Ignore warning messages warnings.filterwarnings("ignore")</pre>
In [3]:	Load Data df=pd.read_csv("insurance.csv")
	Using the histogram and the box plot. We confirm the presence of outliers. So we have to give it special processing. Technically we can give outliers the same treatment as missing values. • Delete those values.
	 Replace them with a statistical measure or by any other value that is in a suitable range. Add new variables, as we mentioned in the EDA. Feature engineering
In [4]:	<pre>class Intervals(): definit(self, feature):</pre>
	<pre>self.mean=feature.mean() self.sd=feature.std()</pre>
	self.interval_range=[1.5,2,2.5,3.0,3.5,4] def Upper_Interval(self):
	<pre>for interval in self.interval_range: upper_interval= self.mean+interval*self.sd</pre>
	<pre>upper_interval=round(upper_interval,2) print(f"Interval range {interval}: {upper_interval}")</pre>
	<pre>def Lower_Interval(self): for interval in self.interval_range:</pre>
	<pre>lower_interval=self.mean-interval*self.sd lower_interval=round(lower_interval,2) print(f"Interval range {interval}: {lower_interval}")</pre>
	We create a class called intervals that have functions that will allow us to make it easier to find the best ideal interval.
In [5]:	<pre>class Best_Interval(Intervals): definit(self, feature):</pre>
	<pre>Intervalsinit(self, feature) def Upper_Interval_Ideal(self):</pre>
	<pre>return super().Upper_Interval() def Lower_Interval_Ideal(self):</pre>
	return super().Lower_Interval() We apply a technique in OOP(Object-oriented programming) to make the code easier to understand. We apply inheritance so that the parent class (Intervals) passes attributes and functions to the child class (Best_Intervals).
In [6]:	Selected from the best interval bmi_interval_ideal=Best_Interval(df["bmi"]) Linear limit PML
In [7]:	<pre>Upper limit BMI bmi_interval_ideal.Upper_Interval_Ideal() Interval range 1.5: 39.81</pre>
	Interval range 2: 42.86 Interval range 2.5: 45.91 Interval range 3.0: 48.96 Interval range 3.5: 52.01 Interval range 4: 55.06
	With an interval of 3 it gives a good value. To be able to replace outliers. **Replaces values greater than the upper range** df["bmi"]=np.where(df["bmi"]>48.95, 48.95, df["bmi"])
In [9]:	Lower limit BMI bmi_interval_ideal.Lower_Interval_Ideal()
	Interval range 1.5: 21.52 Interval range 2: 18.47 Interval range 2.5: 15.42 Interval range 3.0: 12.37
	Interval range 3.5: 9.32 Interval range 4: 6.27 The appropriate interval value is 2. Since considered with the minimum BMI values regardless of sex is 18.
	Replaces values greater than the lower range df["bmi"]=np.where(df["bmi"]<18,18,df["bmi"]) sns_set_style(style="whitegrid")
In [11]:	plt.subplots(1,1,figsize=(20,8)) sns.histplot(data=df,x="bmi")
	plt.show() 140
	120
	40
In [13]:	20 25 30 35 40 45 50 Separate into smokers and non-smokers smoker_no_split=df.query("smoker=='no'")
	smoker_yes_split=df.query("smoker=='yes'") In order to give a better treatment to the data.
	Smoker no split Upper limit Charges charges_interval_ideal=Best_Interval(smoker_no_split["charges"])
In [15]:	<pre>charges_interval_ideal.Upper_Interval_Ideal() Interval range 1.5: 17424.94 Interval range 2: 20421.83</pre>
	Interval range 2.5: 23418.72 Interval range 3.0: 26415.61 Interval range 3.5: 29412.5 Interval range 4: 32409.4
In [16]:	<pre>def scatter_plot_age_charges(dataset): plt.subplots(1,1,figsize=(20,8)) sns.scatterplot(data=dataset, x="age", y="charges")</pre>
In [17]:	<pre>plt.show() scatter_plot_age_charges(dataset=smoker_no_split)</pre>
	35000
	25000
	5000 0 20 30 40 50 60
	Using an interval of 1.5 gives good results. We will use the upper interval to group the degree of medical problem if it is severe or not. Group according to degree of medical problem smoker_no_split["medical_problem"]=smoker_no_split["charges"].apply(lambda x: "severe" if x>17000 else "light")
In [19]:	For those values greater than \$17,000 US, it will classify them as severe medical problems. plt.subplots(1,1,figsize=(20,8))
	<pre>sns.scatterplot(data=smoker_no_split, x="age", y="charges", hue="medical_problem", palette="Set2") plt.show()</pre> <pre></pre>
	35000 severe
	25000 gg 20000
	15000
	20 30 40 50 60 Smoker yes split
In [20]:	scatter_plot_age_charges(dataset=smoker_yes_split)
	50000
	89 40000 Every Company of the Compan
	30000
	2000
In [21]:	20 30 40 50 60 From a range higher than \$32,000 USD we could create a new group, in a similar way to non-smokers but with a different range Smoker_yes_split["medical_problem"]=smoker_yes_split["charges"].apply(lambda x: "severe" if x > 32000 else "light")
In [22]:	<pre>plt.subplots(1,1,figsize=(20,8)) sns.scatterplot(data=smoker_yes_split,x="age",y="charges",hue="medical_problem",palette="Set2")</pre>
	plt.show() medical_problem ight severe
	50000
	8 4000
	20000
	20 30 40 50 60
In [23]:	Replace Outliers Values smoker_yes_split["charges"]=smoker_yes_split["charges"].apply(lambda x: 48000 if x > 48000 else x)
	We replace values greater than \$48,000 and substitute them with that amount, since it is the closest value to the outliers. We create a new dataframe with the clean data ### alloward appoint (Foresteen no. and it appoint appoint appoint to the outliers).
In [25]:	<pre>df_clear=pd.concat([smoker_no_split, smoker_yes_split]) def boxplot():</pre>
	<pre>fig,(ax_box_1,ax_box_2)=plt.subplots(1,2,figsize=(20,8)) ax_box_1.set_title("Adding new feature")</pre>
	<pre>sns.boxplot(data=df_clear, x="smoker",</pre>
	<pre>palette="Set2", ax=ax_box_1) ax_box_2.set_title("Without the new feature")</pre>
	sns.boxplot(data=df, x="smoker", y="charges", palette="Set2",
In [26]:	<pre>ax=ax_box_2) plt.show()</pre>
, - 1 *	Adding new feature Mithout the new feature S0000 Medical_problem Severe S0000 Medical_problem Severe
	40000
	30000
	20000
	no yes yes no
	we save the dataset with the clean data
In [27]:	df_clear.to_csv("insurence_clearv2.csv",index=False)