In [1]:	<pre>import numpy as np import pandas as pd import seaborn as sns import matplotlib.pyplot as plt import statistics from sklearn.model_selection import train_test_split from sklearn.linear_model import LinearRegression from sklearn import metrics from sklearn.tree import DecisionTreeClassifier</pre>
In [2]: Out[2]:	<pre>df = pd.read_csv('Insurance.csv') df.head() age sex</pre>
In [3]: Out[3]:	4 32 1 28.880 0 0 1 3866.85520 1 df.head(30)
	3 33 1 22.705 0 0 1 21984.47061 0 4 32 1 28.880 0 0 1 3866.85520 1 5 31 0 25.740 0 0 2 3756.62160 0 6 46 0 33.440 1 0 2 8240.58960 1 7 37 0 27.740 3 0 1 7281.50560 0 8 37 1 29.830 2 0 0 6406.41070 0 9 60 0 25.840 0 0 1 28923.13692 0
	10 25 1 26.220 0 0 0 2721.32080 1 11 62 0 26.290 0 1 2 27808.72510 1 12 23 1 34.400 0 0 3 1826.84300 1 13 56 0 39.820 0 0 2 11090.71780 1 14 27 1 42.130 0 1 2 39611.75770 1 15 19 1 24.600 1 0 3 1837.23700 0 16 52 0 30.780 1 0 0 10797.33620 1
	17 23 1 23.845 0 0 0 2395.17155 0 18 56 1 40.300 0 0 3 10602.38500 1 19 30 1 35.300 0 1 3 36837.46700 1 20 60 0 36.005 0 0 13228.84695 1 21 30 0 32.400 1 0 3 4149.73600 1 22 18 1 34.100 0 2 1137.01100 1 23 34 0 31.920 1 1 0 37701.87680 1
	24 37 1 28.025 2 0 1 6203.90175 0 25 59 0 27.720 3 0 2 14001.13380 1 26 63 0 23.085 0 0 0 1 12268.63225 0 27 55 0 32.775 2 0 1 12268.63225 0 28 23 1 17.385 1 0 1 2775.19215 1 29 31 1 36.300 2 1 3 38711.00000 1
In [4]:	<pre>df.info() <class 'pandas.core.frame.dataframe'=""> RangeIndex: 1338 entries, 0 to 1337 Data columns (total 8 columns): # Column</class></pre>
In [5]: Out[5]:	5 region 1338 non-null int64 6 charges 1338 non-null float64 7 insuranceclaim 1338 non-null int64 dtypes: float64(2), int64(6) memory usage: 83.8 KB df.describe() age sex bmi children smoker region charges insuranceclaim count 1338.00000 1338.00000 1338.00000 1338.00000 1338.00000 1338.00000 1338.00000 1338.00000 mean 39.207025 0.505232 30.663397 1.094918 0.204783 1.515695 13270.422265 0.585202
	mean 39.207025 0.505232 30.663397 1.094918 0.204783 1.515695 13270.422265 0.585202 std 14.049960 0.500160 6.098187 1.205493 0.403694 1.104885 12110.011237 0.492871 min 18.000000 0.000000 15.960000 0.000000 0.000000 1121.873900 0.000000 25% 27.000000 0.000000 26.296250 0.000000 1.000000 4740.287150 0.000000 50% 39.000000 1.000000 30.40000 1.000000 2.000000 2.000000 1.000000 75% 51.000000 1.000000 5.00000 1.000000 3.00000 5.00000 1.000000 1.000000
In [6]:	df.isnull().sum() age 0 sex 0 bmi 0 children 0 smoker 0 region 0 charges 0 insuranceclaim 0 dtype: int64
Out[8]:	<pre>df.shape (1338, 8) df.size 10704 df.columns Index(['age', 'sex', 'bmi', 'children', 'smoker', 'region', 'charges',</pre>
Out[10]:	<pre>'insuranceclaim'], dtype='object') df['sex'].value_counts() 1 676 0 662 Name: sex, dtype: int64 sns.set() plt.figure(figsize=(6,6)) sns.displot(df['age'])</pre>
	plt.title('age distribution') plt.show() <figure 0="" 600x600="" axes="" size="" with=""> age distribution 200 175</figure>
	150 125 100 75
	50 25 0 20 30 40 50 60 age
In [13]: In [14]:	
Out[14]:	age sex bmi children smoker region charges insuranceclaim age 1.000000 -0.020856 0.109272 0.042469 -0.025019 0.002127 0.299008 0.113723 sex -0.020856 1.00000 0.046371 0.017163 0.076185 0.004588 0.057292 0.031565 bmi 0.109272 0.046371 1.00000 0.012759 0.003750 0.157566 0.198341 0.384198 children 0.042469 0.017163 0.012759 1.00000 0.007673 0.016569 0.067998 -0.409526 smoker -0.025019 0.076185 0.003750 0.002181 0.787251 0.333261 charges 0.299008 0.057292 0.198341 0.006208 0.002081 0.002000 0.309418
In [15]:	insuranceclaim 0.113723 0.031565 0.384198 -0.409526 0.333261 0.020891 0.309418 1.000000 plt.figure(figsize=(6,6)) sns.countplot(x='sex',data=df) plt.title('sex distribution') plt.show() sex distribution 700
	600 500 400
	200 100
In [16]:	<pre>plt.figure(figsize=(6,6)) sns.displot(df['bmi']) plt.title('BMI distribution') plt.show()</pre>
	<pre> <pre> Figure size 600x600 with 0 Axes> BMI distribution 140 120 100</pre></pre>
	80 60 40
In [17]:	plt.figure(figsize=(6,6)) sns.countplot(x='children', data=df)
	plt.title('children') plt.show() children 600 500
	400 time 300
In [18]: Out[18]:	<pre>df['children'].value_counts() 0 574 1 324 2 240 3 157 4 25 5 18 Name: children, dtype: int64</pre>
In [19]:	plt.figure(figsize=(6,6)) sns.countplot(x='smoker',data=df) plt.title('smoker') plt.show() smoker
	800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 - 800 -
	200
Out[20]:	<pre>0</pre>
	plt.ititle('charges distribution') plt.show() C:\Users\Sonali\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms). warnings.warn(msg, FutureWarning) 1e-5
	6 5 Air 4
In [22]:	0 -10000 0 10000 20000 30000 40000 50000 60000 70000 charges X = df.drop(columns='charges', axis=1) Y = df['charges'] print(X) age sex bmi children smoker region insuranceclaim 0 19 0 27.900 0 1 3 1
	1
In [23]:	print(Y) 0
In [31]: In [32]: Out[32]:	age sex bmi children smoker region insuranceclaim 560 46 0 19.950 2 0 1 0
	1285 47 0 24.320 0 0 0 0 1142 52 0 24.860 0 0 2 0 969 39 0 34.320 5 0 2 0 486 54 0 21.470 3 0 1 0 1095 18 0 31.350 4 0 0 0 1130 39 0 23.870 5 0 2 0 1294 58 1 25.175 0 0 0
In [35]:	860 37 0 47.600 2 1 3 1 1126 55 1 29.900 0 0 3 1 1070 rows × 7 columns from sklearn.sym import SVR from sklearn.ensemble import RandomForestRegressor from sklearn.ensemble import GradientBoostingRegressor
Out[36]:	<pre>lr= LinearRegression() lr.fit(X_train, Y_train) svm=SVR() svm.fit(X_train, Y_train) rf= RandomForestRegressor() rf.fit(X_train, Y_train) gr=GradientBoostingRegressor() gr.fit(X_train, Y_train) GradientBoostingRegressor()</pre> <pre>Y_pred1 = lr.predict(X_test)</pre>
In [42]: Out[42]:	<pre>Y_pred2 =svm.predict(X_test) Y_pred3 =rf.predict(X_test) Y_pred4 =gr.predict(X_test) df1 = pd.DataFrame({'Actual': Y_test,'Lr': Y_pred1,'svm':Y_pred2,'rf':Y_pred3,'gr': Y_pred4})</pre>
	887 5272.17580 6532.953193 9497.254380 5268.904884 5829.271736 890 29330.98315 37069.034525 9645.823319 28363.092036 27532.354796 1293 9301.89355 7903.623482 9556.241924 10923.492179 9743.834159 259 33750.29180 27160.887292 9427.256466 34591.833691 33626.881814 109 47055.53210 39693.372730 9645.836943 46888.208819 45727.511007 575 12222.89830 11224.198269 9623.037214 12145.653105 12365.233685
	535 6067.12675 8410.955106 9508.142238 6505.093226 6798.054543 543 63770.42801 42111.654361 9604.068774 46682.190209 47981.343043 846 9872.70100 11651.236659 9590.166857 9653.774523 10374.446527 268 rows × 5 columns plt.subplot(221) plt.plot(df1['Actual'].iloc[0:11],label='Actual') plt.plot(df1['Lr'].iloc[0:11],label="Lr")
Out[44]:	plt.legend() <matplotlib.legend.legend 0x2847ce00b80="" at=""> 30000 20000 Actual Lr 10000</matplotlib.legend.legend>
In [46]:	<pre>plt.subplot(221) plt.plot(df1['Actual'].iloc[0:11], label='Actual') plt.plot(df1['Lr'].iloc[0:11], label="Lr") plt.legend() plt.subplot(222)</pre>
	<pre>plt.plot(df1['Actual'].iloc[0:11], label='Actual') plt.plot(df1['svm'].iloc[0:11], label="svr") plt.legend() plt.subplot(223) plt.plot(df1['Actual'].iloc[0:11], label='Actual') plt.plot(df1['rf'].iloc[0:11], label="rf") plt.legend() plt.subplot(224) plt.plot(df1['Actual'].iloc[0:11], label='Actual') plt.plot(df1['yctual'].iloc[0:11], label='Actual') plt.plot(df1['gr'].iloc[0:11], label="gr")</pre>
Out[46]:	plt.legend() <matplotlib.legend.legend 0x2847b573760="" at=""> 30000 Actual 20000 Actual</matplotlib.legend.legend>
	10000 250 500 750 1000 1250 250 500 750 1000 1250 30000
In [47 ¹ ·	20000 Actual gr 10000 10000 250 500 750 1000 1250 250 500 750 1000 1250 from sklearn import metrics
In [48]:	<pre>score1 =metrics.r2_score(Y_test, Y_pred1) score2 =metrics.r2_score(Y_test, Y_pred2) score3 =metrics.r2_score(Y_test, Y_pred3) score4 =metrics.r2_score(Y_test, Y_pred4) print(score1, score2, score3, score4) 0.7824434217148323 -0.07236455414008303 0.8625838436393364 0.8785486163733124 s1= metrics.mean_absolute_error(Y_test, Y_pred1)</pre>
In [53]:	s2= metrics.mean_absolute_error(Y_test,Y_pred2) s2= metrics.mean_absolute_error(Y_test,Y_pred3) s4= metrics.mean_absolute_error(Y_test,Y_pred3) print(s1,s2,s3,s4) 4202.073483424077 8594.784126770652 2547.505711386106 2547.505711386106 # from this different evaluation we conclude that the 4th model is the best method for this dataset. For prediction and absolute error # Gradient Boosting Regressor is best for this model.