Predicting insurance charges based on the provided dataset falls under the realm of Supervised Machine Learning, specifically Regression. Here's why:

Supervised Learning: In supervised learning, you have a labeled dataset, which means you have input features (in this case, age, sex, bmi, children, smoker) and a corresponding target variable (in this case, charges). Your goal is to predict the target variable based on the input features. In this case, you want to predict insurance charges (target variable) based on the parameters provided (input features).

Regression: In regression, the target variable is continuous, which is the case here with insurance charges. You aim to find a relationship between the input features and the continuous target variable to make predictions.

Classification: This problem is not a classification problem because classification is used when you want to assign data points to specific categories or classes. In this case, you are not categorizing data into predefined classes; instead, you are predicting a numerical value (insurance charges).

There are “1338 Rows x 6 Columns”

Nominal Data:

Nominal data, also known as categorical data, represents categories or labels that do not have any inherent order or ranking. These categories are typically qualitative in nature and cannot be mathematically ranked or compared.

Examples of nominal data include categories like colors, types of fruits, gender (male, female, other), or car makes (e.g., Ford, Toyota, Honda).

Nominal data can be used to group or classify items, but you cannot perform arithmetic operations on them or establish any meaningful order between the categories.

Ordinal Data:

Ordinal data, like nominal data, represents categories, but the key difference is that ordinal data categories have a meaningful order or ranking associated with them. While the intervals between the categories are not consistent, we know that one category is higher or lower than another.

Examples of ordinal data include survey responses with options like "strongly agree," "agree," "neutral," "disagree," and "strongly disagree." There's a clear order in terms of agreement level, but the differences between these categories are not necessarily uniform.

In ordinal data, you can perform operations like comparing which category is higher or lower, but you cannot determine the exact magnitude of the difference between categories.

To find the following the machine learning regression method using in r2 value

Multiple Linear Regression (R2 Value) = 0.78

Support Vector Machine:

S.No.	Hyper Parameter	Linear (r2 Value)	RBF (Non-Linear) (r2 Value)	POLY (r2 Value)	Sigmoid (r2 Value)
1	C3000	0.74	0.86	0.85	-2.12
2	C2000	0.74	0.85	0.86	-0.59
3	C1000	0.76	0.81	0.85	0.28
4	C500	0.76	0.66	0.82	0.44
5	C300	0.68	0.55	0.79	0.50
6	C200	0.63	0.47	0.75	0.54

The SVM Regression use R2 Value (POLY and hyper parameter C2000) = 0.86

The SVM Regression use R2 Value (RBF and hyper parameter C3000) = 0.86

Decision Tree

S.No	Criterion	Max Features	Splitter	R2 Value
1	Squared_error	Sqrt	Best	0.72
2	Squared_error	Log2	Radom	0.72
3	Mse	Log2	Best	0.71
4	Mse	Sqrt	Random	0.70
5	Friedman_mse	Log2	Best	0.70
6	Friedman_mse	Auto	Random	0.67

The Decision Tree regression use R2 value (criterion=squared_error,max_features=sqrt, and splitter=random) = 0.72

The Decision Tree regression use R2 value (criterion=squared_error,max_features=log2, and splitter=random) = 0.72

Random Forest

S.No	Criterion	N_estimators	Max_features	Random_state	R2 Value
1	Mse	100	Sqrt	0	0.87
2	Mse	100	Log2	0	0.87

The Random Forest Regression use R2 value (criterion = mse, n_estimators = 100, max_features = sqrt & log2) = 0.87

The Final Best Model

The Random Forest Regression use R2 value (criterion = mse, n_estimators = 100, max_features = sqrt & log2) = 0.87