

Prediction of Salary Class of an Individual

Problem:

The problem is to predict the salaried class of an individual is greater than \$50,000 or less than \$50,000 based on an individual's credentials like education level, age, gender, experience, occupation, etc. For example, the salary of an individual whose experience is above 15 years is most likely to be greater than \$50,000. Prediction is not made by considering only one factor but all the factors that affect the income of an individual.

About Dataset:

The dataset is taken from Kaggle. The US Adult Census dataset is a repository of 32,561 entries with 15 variables. The dataset contains information about age, work class, education, occupation, relationship, country, income. Let's look at dataset details.

	age	workclass	fnlwgt	education	education.num	marital.status	occupation	relationship	race	sex	capital.gain	capital.loss	hours.per.week	native.country	income
1	90	?	77053	HS-grad	9	Widowed	?	Not-in-family	White	Female	0	4356	40	United-States	<=50K
2	82	Private	132870	HS-grad	9	Widowed	Exec-managerial	Not-in-family	White	Female	0	4356	18	United-States	<=50K
3	66	?	186061	Some-college	10	Widowed	?	Unmarried	Black	Female	0	4356	40	United-States	<=50K
4	54	Private	140359	7th-8th	4	Divorced	Machine-op-inspct	Unmarried	White	Female	0	3900	40	United-States	<=50K
5	41	Private	264663	Some-college	10	Separated	Prof-specialty	Own-child	White	Female	0	3900	40	United-States	<=50K
6	34	Private	216864	HS-grad	9	Divorced	Other-service	Unmarried	White	Female	0	3770	45	United-States	<=50K
7	38	Private	150601	10th	6	Separated	Adm-clerical	Unmarried	White	Male	0	3770	40	United-States	<=50K
8	74	State-gov	88638	Doctorate	16	Never-married	Prof-specialty	Other-relative	White	Female	0	3683	20	United-States	>50K
9	68	Federal-gov	422013	HS-grad	9	Divorced	Prof-specialty	Not-in-family	White	Female	0	3683	40	United-States	<=50K
10	41	Private	70037	Some-college	10	Never-married	Craft-repair	Unmarried	White	Male	0	3004	60	?	>50K
11	45	Private	172274	Doctorate	16	Divorced	Prof-specialty	Unmarried	Black	Female	0	3004	35	United-States	>50K
12	38	Self-emp-not-inc	164526	Prof-school	15	Never-married	Prof-specialty	Not-in-family	White	Male	0	2824	45	United-States	>50K
13	52	Private	129177	Bachelors	13	Widowed	Other-service	Not-in-family	White	Female	0	2824	20	United-States	>50K
14	32	Private	136204	Masters	14	Separated	Exec-managerial	Not-in-family	White	Male	0	2824	55	United-States	>50K
15	51	?	172175	Doctorate	16	Never-married	?	Not-in-family	White	Male	0	2824	40	United-States	>50K
16	46	Private	45363	Prof-school	15	Divorced	Prof-specialty	Not-in-family	White	Male	0	2824	40	United-States	>50K
17	45	Private	172822	11th	7	Divorced	Transport-moving	Not-in-family	White	Male	0	2824	76	United-States	>50K
18	57	Private	317847	Masters	14	Divorced	Exec-managerial	Not-in-family	White	Male	0	2824	50	United-States	>50K
19	22	Private	119592	Assoc-acdm	12	Never-married	Handlers-cleaners	Not-in-family	Black	Male	0	2824	40	?	>50K

Here is the link of Dataset: [Adult Census Income | Kaggle](#)

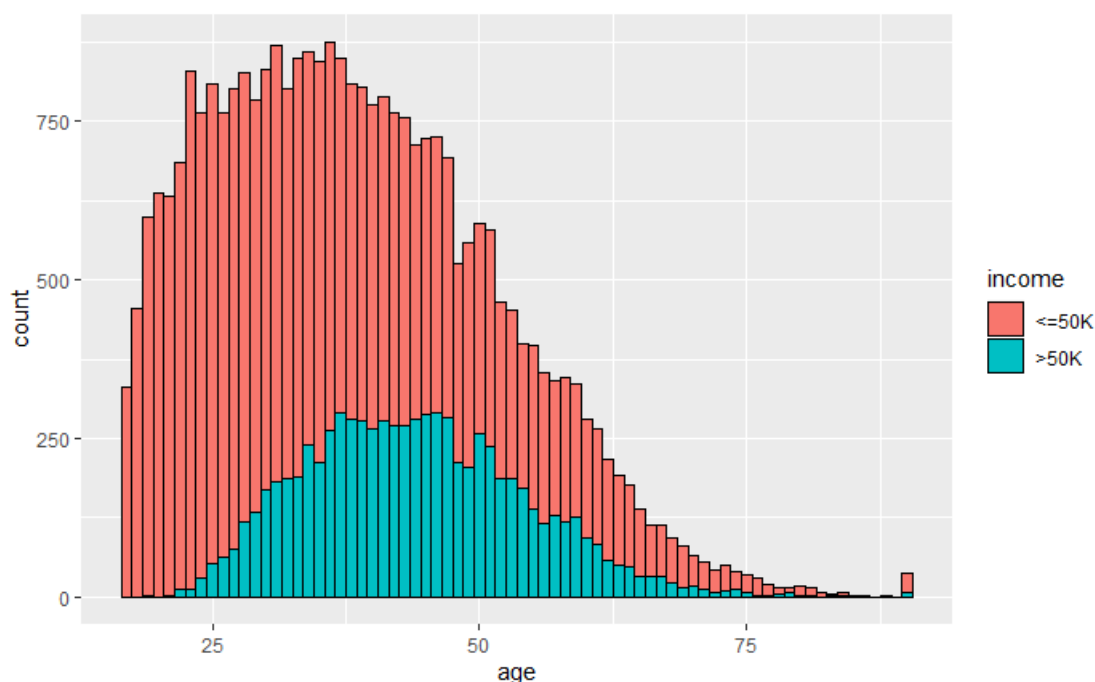
Approach:

As this is the prediction problem, we can use the Naive Bayes method, Linear Regression and Logistic Regression. The prediction variable (salary class) depends on various variables (both categorical and Numeric), So the Naive Bayes method and Logistic Regression are the best for this problem compared to the Linear Regression. Our dataset has more categorical variables compared to numerical variables, so Logistic Regression is the best suitable solution for this problem.

Logistic Regression: Logistic regression is one of the most popular Machine Learning algorithms, which comes under the Supervised Learning technique. It is used for predicting the categorical dependent variable using a given set of independent variables. Therefore, the outcome must be a categorical or discrete value. It can be either Yes or No, 0 or 1, true or False, etc. but instead of giving the exact value as 0 and 1, **it gives the probabilistic values which lie between 0 and 1.**

Analysis:

From the graph below we can say that the original dataset contains a distribution of 25% entries labelled with >50k and 75% entries labelled with <=50k.



The first step we took was to visualize the distribution of each variable and its effect on the likelihood of earning more than \$50,000 per year. From our analysis, we concluded that the most useful variables for prediction were age, education, hours per week, occupation, and sex. That means We can say that age, education, hours per week, occupation, and sex are the variables that are going to impact the salary of an individual. So, to predict we should consider all these variables and develop our model.

Results:

As this is a prediction problem Accuracy is the measure to find how our model is predicting the salaried class of an individual. The accuracy of the model is shown below.

	FALSE	TRUE
<=50K	5627	140
>50K	1190	722

$$\begin{aligned}
 \text{Accuracy} &= (\text{Correct predictions}) / (\text{Total predictions}) \\
 &= (5627+722) / (5627+140+1190+722) \\
 &= 6349 / 7679 \\
 &= 0.8268
 \end{aligned}$$

The accuracy of our model is 82.68% to predict the salary class of an individual by considering age, education, hours per week, occupation, and sex as categorical variables.

Conclusions:

From the results, we can conclude that the salary of an individual whose income is greater than \$50,000 is male, whose education level is higher than a master's degree and who works more than 40 hours per week, and whose occupation is in the private sector.

GitHub link: https://github.com/Tarak477/64060_tnunna.git