International Journal of Scientific Research & Engineering Trends
Volume 6, Issue 6, Nov-Dec-2020, ISSN (Online): 2395-566X

Income Analysis of Census Database Using Pyspark

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***Abstract*-The data set contains information about every individual's age, education level and various other features from the census along with the income . The income feature is a categorical feature with two classes i.e., less than 50k dollars or greater than 50k dollars. The problem is to build a machine learning model that could effectively predict the income of people given the input features. Considering the size of the data and the dimension of the data, the model is built using Big Data Techniques.**

***Keywords*-census income dataset python, census income dataset kaggle, census income dataset project, census data kaggle.**

I.INTRODUCTION

1. Data set source:
This data was extracted from the census bureau database found at https://archive.ics.uci.edu/ml/datasets/adult

2. Data set Attributes:
2.1 Age- continuous.
2.2 Workclass- Private, Self-emp-not-inc, Self-emp-inc, Federal-gov, Local-gov, State-gov, Without-pay, Never-worked.
2.3 Fnlwgt- continuous. The weights on the CPS files are controlled to independent estimates of the civilian noninstitutional population of the US. These are prepared monthly for us by Population Division here at the Census Bureau. We use 3 sets of controls.
These are:

- A single cell estimate of the population 16+ for each state.
- Controls for Hispanic Origin by age and sex.
- Controls by Race, age and sex.
- We use all three sets of controls in our weighting program and "rake" through them 6 times so that by the end we come back to all the controls we used. The term estimate refers to population totals derived from CPS by creating "weighted tallies" of any specified socio-economic characteristics of the population.
- People with similar demographic characteristics should have similar weights. There is one important caveat to remember about this statement. That is that since the CPS sample is actually a collection of 51 state samples, each with its own probability of selection, the statement only applies within state.
- education: Bachelors, Some-college, 11th, HS-grad, Prof-school, Assoc-acdm, Assoc-voc, 9th, 7th-8th, 12th, Masters, 1st-4th, 10th, Doctorate, 5th-6th, Preschool.

3. Education-num: continuous.
3.1 Marital-status: Married-civ-spouse, Divorced, Never-married, Separated, Widowed, Married-spouse-absent, Married-AF-spouse.
3.2 Occupation: Tech-support, Craft-repair, Other-service, Sales, Exec-managerial, Prof-specialty, Handlers-cleaners, Machine-op-inspct, Adm-clerical, Farming-fishing, Transport-moving, Priv-house-serv, Protective-serv, Armed-Forces.
3.3 Relationship: Wife, Own-child, Husband, Not-in-family, Other-relative, Unmarried.
3.3 Race: White, Asian-Pac-Islander, Amer-Indian-Eskimo, Other, Black.
3.4 Sex: Female, Male.
3.5 Capital-gain: continuous.
3.6 capital-loss: continuous.
4 Hours-per-week: continuous.
Native-country: United-States, Cambodia, England, Puerto-Rico, Canada, Germany, Outlying-US(Guam-USVI-etc), India, Japan, Greece, South, China, Cuba, Iran, Honduras, Philippines, Italy, Poland, Jamaica, Vietnam, Mexico, Portugal, Ireland, France, Dominican-Republic, Laos, Ecuador, Taiwan, Haiti, Columbia, Hungary, Guatemala, Nicaragua, Scotland, Thailand, Yugoslavia, El-Salvador, Trinadad&Tobago, Peru, Hong, Holand-Netherlands.
income:>50K, <=50K.

5. Dataset Sample:

age	workclass	fnlwgt	education	education	marital_status	occupation	relationship	race	sex	capital_gain	capital_loss	hours_per	native_country	income
39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40	United-States	<=50K
50	Self-emp-n	83311	Bachelors	13	Married-civ-spc	Exec-manage	Husband	White	Male	0	0	13	United-States	<=50K
38	Private	215646	HS-grad	9	Divorced	Handlers-cle	Not-in-family	White	Male	0	0	40	United-States	<=50K
53	Private	234721	11th	7	Married-civ-spc	Handlers-cle	Husband	Black	Male	0	0	40	United-States	<=50K
28	Private	338409	Bachelors	13	Married-civ-spc	Prof-specialt	Wife	Black	Female	0	0	40	Cuba	<=50K
37	Private	284582	Masters	14	Married-civ-spc	Exec-manage	Wife	White	Female	0	0	40	United-States	<=50K
49	Private	160187	9th	5	Married-spouse	Other-service	Not-in-family	Black	Female	0	0	16	Jamaica	<=50K
52	Self-emp-n	209642	HS-grad	9	Married-civ-spc	Exec-manage	Husband	White	Male	0	0	45	United-States	>50K
31	Private	45781	Masters	14	Never-married	Prof-specialt	Not-in-family	White	Female	14084	0	50	United-States	>50K

Fig 1 : Sample Dataset

6. Tools Used:

- Python
- Apache Spark MLlib
- Apache Spark SQL
- Pyspark
- Hive

II. TECHNIQUES AND METHODOLOGY

1. Creation of Spark Session and reading the data:

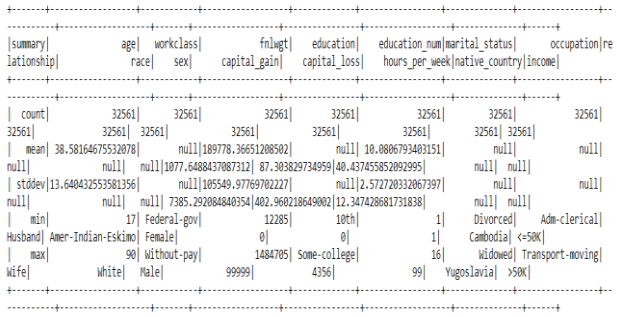
A spark session is firstly initialized. The entry point into all functionality in Spark is the SparkSession class. SparkSession in Spark 2.0 provides builtin support for Hive features including the ability to write queries using HiveQL, access to Hive UDFs, and the ability to read data from Hive tables. To use these features, we do not need to have an existing Hive setup. After creating the spark session, the data is read in the form of RDD (Resilient Distributed Dataset). Resilient Distributed Datasets (RDD) is a fundamental data structure of Spark. It is an immutable distributed collection of objects. Each dataset in RDD is divided into logical partitions, which may be computed on different nodes of the cluster.

```
root
 |-- age: integer (nullable = true)
 |-- workclass: string (nullable = true)
 |-- fnlwgt: integer (nullable = true)
 |-- education: string (nullable = true)
 |-- education_num: integer (nullable = true)
 |-- marital_status: string (nullable = true)
 |-- occupation: string (nullable = true)
 |-- relationship: string (nullable = true)
 |-- race: string (nullable = true)
 |-- sex: string (nullable = true)
 |-- capital_gain: integer (nullable = true)
 |-- capital_loss: integer (nullable = true)
 |-- hours_per_week: integer (nullable = true)
 |-- native_country: string (nullable = true)
 |-- income: string (nullable = true)
```

Fig 2. Schema of data

2. Descriptive statistics of the data:

The descriptive statistics include the mean, median , standard deviation , count, minimum and maximum values for each attribute.



summary	age	workclass	fnlwgt	education	education_num	marital_status	occupation	relationship	race	sex	capital_gain	capital_loss	hours_per_week	native_country	income
count	32561	32561	32561	32561	32561	32561	32561	32561	32561	32561	32561	32561	32561	32561	32561
mean	38.58164675532078	null	189778.36651208502	null	10.0806793403151	null	null	null	null	null	1077.6488437087312	87.303829734959	40.437455852092995	null	null
stddev	13.640432553581356	null	105549.97769702227	null	2.572720332067397	null	null	null	null	null	7385.292084840354	402.960218649002	12.347428681731838	null	null
min	17	Federal-gov	12285	10th	1	Divorced	Adm-clerical	Husband	Amer-Indian-Eskimo	Female	0	0	1	Cambodia	<=50K
max	90	Without-pay	1484705	Some-college	16	Widowed	Transport-moving	Wife	White	Male	99999	4356	99	Yugoslavia	>50K

Fig 3. Descriptive statistics

III. EXPLORATORY DATA ANALYSIS AND DATA UNDERSTANDING

Initially a view for the data is created. After performing various type of querying on the data, an overall picture of the data and the distribution of values in the data is obtained

workclass	avg(hours_per_week)	avg(capital_loss)	avg(capital_gain)
State-gov	39.03158705701079	83.25654853620955	701.6995377503852
Federal-gov	41.37916666666667	112.26875	833.2322916666667
Self-emp-not-inc	44.421881149153876	116.63164108618655	1886.0617866981504
Local-gov	40.98279980888677	109.85427615862399	880.202580028667
Private	39.64234469264634	78.56815587803685	868.0810370128811
Self-emp-inc	48.81810035842294	155.13888888888889	4875.693548387097
Without-pay	32.714285714285715	0.0	487.85714285714283
Never-worked	28.428571428571427	0.0	0.0

Fig 4. Aggregated output of workclass

From fig 4 we can see that Self employed people who tend to spend more working hours a week have less capital loss and more capital gain people who work in Local Govt tend to have more capital loss for their capital gain

income	avg(hours_per_week)	avg(capital_loss)	avg(capital_gain)
>50K	45.473026399693914	195.00153041703865	4006.142456319347
<=50K	38.840210355987054	53.142920711974 11	148.75246763754046

Fig 5. Aggregated output of income

From fig 5 we can see that people who earn more than 50k dollars tend to work longer and there is a huge difference in the average capital gains of people who earn less than 50k dollars and greater than 50k dollars per year.

occupation	avg(hours_per_week)	avg(capital_gain)	avg(capital_loss)
Farming-fishing	46.989939637826964	589.7263581488934	63.07545271629779
Handlers-cleaners	37.947445255474456	257.5729927007299	45.635766423357666
Prof-specialty	39.15828179842888	2072.9755975263247	112.84857095102791
Adm-clerical	37.55835543766578	495.9549071618037	60.794429708222815
Exec-managerial	44.9877029021151	2262.7729955730447	138.83841613379244
Craft-repair	42.30422054159551	649.5128080019517	88.46523542327397
Sales	40.78109589041096	1319.829315068493	98.30054794520548
Tech-support	39.432112068965516	673.5528017241379	98.66594827586206
Transport-moving	44.65623043206011	490.3237319974953	81.48090169067001
Protective-serv	42.87057010785824	708.0986132511556	78.33436055469954
Armed-Forces	40.666666666666664	0.0	209.66666666666666
Machine-op-inspct	40.755744255744254	328.6893106893107	61.70629370629371
Other-service	34.70166919575114	191.30166919575115	38.25068285280729
Priv-house-serv	32.88590604026846	279.8523489932886	21.449664429530202

Fig 6. Aggregated output of occupation

From fig 6 we can see that people who work in farming and fishing tend to work for more hours in a week and yet don't get capital gain as much as people who work in other sectors. Similarly people who work in transportation sector also don't get paid as much as people from higher sectors in spite of working for more than 46 hours a week.

sex	avg(hours_per_week)	avg(capital_gain)	avg(capital_loss)
Male	42.42808627810923	1329.3700780174393	100.21330885727397
Female	36.410361154953115	568.4105468387336	61.18763346021725

Fig 7. Aggregated output of sex

Fig 7 tells us that the average capital gain of males is very high when compared to that of females.

education	avg(hours_per_week)	avg(capital_gain)	avg(capital_loss)
Prof-school	47.42534722222222	10414.416666666666	231.203125
10th	37.052518756698824	404.57449088960345	56.845659163987136
7th-8th	39.36687306501548	233.93962848297213	65.6687306501548
5th-6th	38.89789789789979	176.02102102102103	68.25225225225225
Assoc-acdm	40.504217432052485	640.3992502343018	93.41893158388004
Assoc-voc	41.61070911722142	715.0513748191028	72.75470332850941
Masters	43.83633197910621	2562.563551944283	166.71967498549043
12th	35.78060046189376	284.0877598152425	32.33718244803695
Preschool	36.64705882352941	898.3921568627451	66.49019607843137
9th	38.04474708171206	342.08949416342415	28.99805447470817
Bachelors	42.614005602240894	1756.299533146592	118.35032679738562
Doctorate	46.973365617433416	4770.145278450364	262.8450363196126
HS-grad	40.575373773926295	576.800114274831	70.46662222645462
11th	33.92595744680851	215.09787234042554	50.07914893617021
Some-college	38.85228363736113	598.8241667809629	71.63708681936635
1st-4th	38.25595238095238	125.875	48.32738095238095

Fig 8. Aggregated output of education

Fig 8 tells us that people with higher education, tend to work less and yet gain more income while people with poor education tend to work longer hours and yet could not earn much.

IV. DATA PREPROCESSING

1. Checking for missing values:

age	workclass	fnlwgt	education	education_num	marital_status	occupation	relationship	race	sex	capital_gain	capital_loss	hours_per_week	native_country	income
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Fig 9. Missing value in each catagory

From fig 9 we can see that that we thankfully don't have any missing values to be handled

2. Distinct categories in each attribute:

workclass	education	marital_status	occupation	relationship	race	native_country
8	16	7	14	6	5	41

Fig 10. Distinct catagories in each attribute

Fig 10 tells us the number of distinct classes in each feature

3.String Indexing:

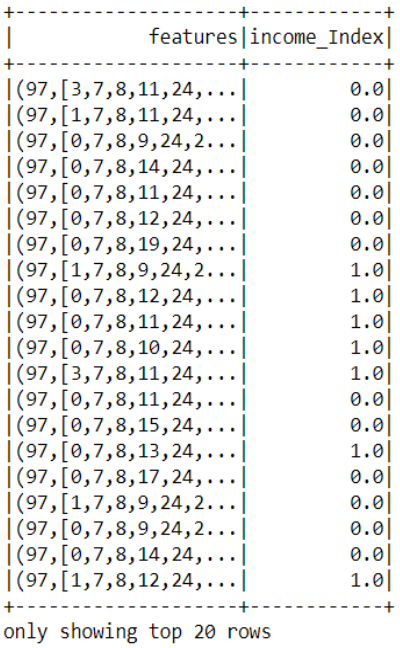
StringIndexer encodes a string column of labels to a column of label indices. StringIndexer can encode multiple columns.

4.One Hot Encoding:

One-hot encoding maps a categorical feature, represented as a label index, to a binary vector with at most a single one-value indicating the presence of a specific feature value from among the set of all feature values. This encoding allows algorithms which expect continuous features, such as Logistic Regression, to use categorical features. For string type input data, it is common to encode categorical features using StringIndexer first. One Hot Encoder can transform multiple columns, returning an one-hot-encoded output vector column for each input column. It is common to merge these vectors into a single feature vector using VectorAssembler.

5. Vector Assembling:

VectorAssembler is a transformer that combines a given list of columns into a single vector column. It is useful for combining raw features and features generated by different feature transformers into a single feature vector, in order to train ML models like logistic regression and decision trees. VectorAssembler accepts the following input column types: all numeric types, boolean type, and vector type. In each row, the values of the input columns will be concatenated into a vector in the specified order.



features	income_Index
(97,[3,7,8,11,24,...	0.0
(97,[1,7,8,11,24,...	0.0
(97,[0,7,8,9,24,2...	0.0
(97,[0,7,8,14,24,...	0.0
(97,[0,7,8,11,24,...	0.0
(97,[0,7,8,12,24,...	0.0
(97,[0,7,8,19,24,...	0.0
(97,[1,7,8,9,24,2...	1.0
(97,[0,7,8,12,24,...	1.0
(97,[0,7,8,11,24,...	1.0
(97,[0,7,8,10,24,...	1.0
(97,[3,7,8,11,24,...	1.0
(97,[0,7,8,11,24,...	0.0
(97,[0,7,8,15,24,...	0.0
(97,[0,7,8,13,24,...	1.0
(97,[0,7,8,17,24,...	0.0
(97,[1,7,8,9,24,2...	0.0
(97,[0,7,8,9,24,2...	0.0
(97,[0,7,8,14,24,...	0.0
(97,[1,7,8,12,24,...	1.0

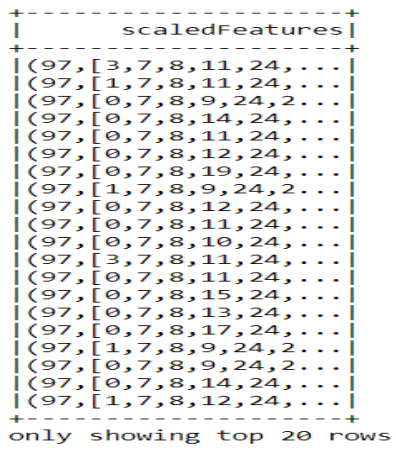
only showing top 20 rows

Fig 11. Vectorized data sample

Fig 11 shows the final data after string indexing , one hot encoding and vector assembling.

6. Standard Scaling:

StandardScaler transforms a dataset of Vector rows, normalizing each feature to have unit standard deviation and/or zero mean



scaledFeatures
(97,[3,7,8,11,24,...
(97,[1,7,8,11,24,...
(97,[0,7,8,9,24,2...
(97,[0,7,8,14,24,...
(97,[0,7,8,11,24,...
(97,[0,7,8,12,24,...
(97,[0,7,8,19,24,...
(97,[1,7,8,9,24,2...
(97,[0,7,8,12,24,...
(97,[0,7,8,11,24,...
(97,[0,7,8,10,24,...
(97,[3,7,8,11,24,...
(97,[0,7,8,11,24,...
(97,[0,7,8,15,24,...
(97,[0,7,8,13,24,...
(97,[0,7,8,17,24,...
(97,[1,7,8,9,24,2...
(97,[0,7,8,9,24,2...
(97,[0,7,8,14,24,...
(97,[1,7,8,12,24,...

only showing top 20 rows

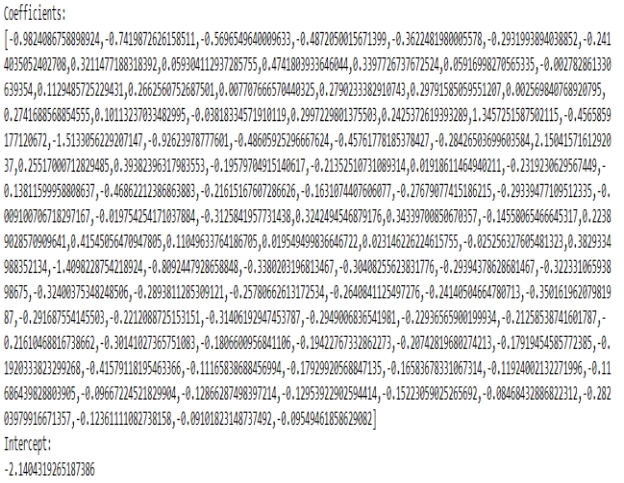
Fig 12. Scaled data sample

Fig 12 shows the data after performing scaling

V. MODEL BUILDING

1. Logistic regression:

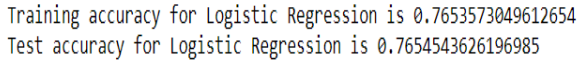
Logistic regression is a popular method to predict a categorical response. It is a special case of Generalized Linear models that predicts the probability of the outcomes. In spark.ml logistic regression can be used to predict a binary outcome by using binomial logistic regression, or it can be used to predict a multiclass outcome by using multinomial logistic regression. After fitting logistic regression to the data, the following coefficients and intercepts are obtained.



Coefficients:
[-0.9824086758898924,-0.7419872626158511,-0.5696549640009633,-0.4872050015671399,-0.3622481980005578,-0.2931993894038852,-0.241
4035052402708,0.3211477188318392,0.05930411293728575,0.4741803933646044,0.3397726737672524,0.05916998270565335,-0.002782861330
639354,0.11294857252294 31,0.2662560752687501,0.007707666570440325,0.2790233382910743,0.2979158505955120 7,0.00256984076892079 5,
0.2741688568854555,0.10113237033482995,-0.038183345719101 19,0.29972298013755 03,0.24253726193932 89,1.345725158750211 5,-0.4565859
177120672,-1.5133056229207147,-0.9262397877760 1,-0.4860592529666762 4,-0.4576177818537842 7,-0.2842650369960358 4,2.150415716129 20
37,0.2551700071282948 5,0.3938239631798355 3,-0.1957970491514061 7,-0.2135251073108931 4,0.01918611464940211,-0.2319230629567449,-
0.1381159995808863 7,-0.4686221238686388 3,-0.2161516760728662 6,-0.1631074407606807 7,-0.2767907741518621 5,-0.2933947710951233 5,-0.
009100706718297167,-0.01975425417103788 4,-0.3125841957731438,0.3242494546879176,0.3433970085067035 7,-0.1455806546664531 7,0.2238
902857090964 1,0.4154505647094780 5,0.1104963376418670 5,0.0195494998364672 2,0.0231462622461575 5,-0.0252563276054813 23,0.3829334
988352134,-1.4098228754218924,-0.8092447928658848,-0.3380203196813467,-0.3040825562383177 6,-0.2939437062868146 7,-0.3223310659 38
98675,-0.3240037534824850 6,-0.2893811285309121,-0.2578066261317253 4,-0.2640841125497276,-0.2414050466478071 3,-0.3501619620798 19
87,-0.2916875541455 03,-0.2212088725153151,-0.3140619294745378 7,-0.2949006836541981,-0.2293656590019993 4,-0.2125853874160178 7,-
0.2161046881673866 2,-0.3014102736575108 3,-0.1806600956841106,-0.1942276733286227 3,-0.2074281968027421 3,-0.1791945458772385,-0.
1920333382299268,-0.4157911819546336 6,-0.1116583868856994,-0.1792992056884713 5,-0.1658367833106731 4,-0.1192400213227196,-0.11
686439828803905,-0.0966724521829904,-0.1286628749839721 4,-0.1295392290259441 4,-0.1522305902526569 2,-0.0846843288682231 2,-0.282
039799166713 57,-0.1236111108273815 8,-0.0910182314873749 2,-0.0954946185862908 2]
Intercept:
-2.140431926518 7386

Fig 13. Coefficient and intercepts of logistic regression

The training and test accuracy of logistic regression is as follows:



Training accuracy for Logistic Regression is 0.7653573049612654
Test accuracy for Logistic Regression is 0.7654543626196985

Fig 14. Accuracy score of logistic regression

From the above output it is clear that the training accuracy is 76% and the test accuracy is also 76% . This is not an acceptable performance. This can be improved by using other algorithms

2. Linear Support Vector Machines:

The linear SVM is a standard method for large-scale classification tasks. It is a linear method as described above in equation (1), with the loss function in the formulation given by the hinge loss:

$L(w;x,y):=\max\{0,1-ywTx\}$.

By default, linear SVMs are trained with an L2 regularization. We also support alternative L1 regularization. In this case, the problem becomes a linear program. The linear SVMs algorithm outputs an SVM model. Given a new data point, denoted by x, the model makes predictions based on the value of wTx. By the default, if $wTx \geq 0$ then the outcome is positive, and negative otherwise.

The following are the coefficients and intercepts of linear SVM:

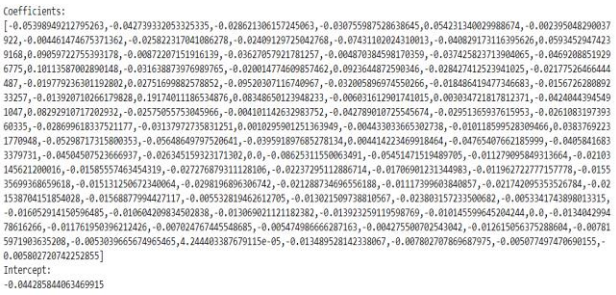


Fig 15. Coefficient and intercept of linear SVM

The training and test accuracy of linear SVM are as follows:

```
Training accuracy for Linear support vector classifier is 0.7653573049612654
Test accuracy for Linear support vector classifier is 0.7654543626196985
```

Fig 16. Accuracy score of linear SVM

Linear SVM also does not tend to improve accuracy much.

3.Decision Tree:

Decision trees are a popular family of classification and regression methods. More information about the spark.ml implementation can be found further in the section on decision trees.A decision tree is a flowchart-like structure in which each internal node represents a "test" on an attribute (e.g. whether a coin flip comes up heads or tails), each branch represents the outcome of the test, and each leaf node represents a class label (decision taken after computing all attributes). The paths from root to leaf represent classification rules.In decision analysis, a decision tree and the closely related influence diagram are used as a visual and analytical decision support tool, where the expected values (or expected utility) of competing alternatives are calculated.

The training and test accuracy of Decision Tree is below:

```
Training accuracy for decision tree is 0.839551
Test accuracy for decision tree is 0.83959
```

Fig 17. Accuracy score of Decision tree

The performance of the decision tree is better than both logistic regression and linear SVM but this can still be improved.

4. Random Forest:

Random forests or random decision forests are an ensemble learning method for classification, regression and other tasks that operate by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes (classification) or mean/average prediction (regression) of the individual trees. Random decision forests correct for decision trees' habit of overfitting to their training set. Random forests generally outperform decision trees, but their accuracy is lower than gradient boosted trees. However, data characteristics can affect their performance. The training and test accuracy for Random forest is as follows:

```
Training accuracy for Random forest with 200 trees is 0.876151
Trest accuracy for Random forest with 200 trees is 0.853693
```

Fig 18. Accuracy score of random forest

From fig 18 we can see that the training and test accuracy is much higher than the decision tree classifier. In order to obtain a better accuracy , Gradient-boosted tree classifier can be tried.

5. Gradient-boosted tree classifier:

Gradient boosting refers to a class of ensemble machine learning algorithms that can be used for classification or regression predictive modeling problems. Gradient boosting is also known as gradient tree boosting, stochastic gradient boosting (an extension), and gradient boosting machines, or GBM for short.Ensembles are constructed from decision tree models. Trees are added one at a time to the ensemble and fit to correct the prediction errors made by prior models. This is a type of ensemble machine learning model referred to as boosting.

The training and test accuracy of GBT is as follows:

```
Training accuracy for gradient boosted tree is 0.960141
Test accuracy for gradient boosted tree  0.829343
```

Fig 19. Accuracy score of Gradient – boosted tree

VI. OVERALL INFERENCE

After performing the above algorithms, we obtained the following accuracies

Table 1. Overall accuracy comparison table

Model	Training Accuracy	Test Accuracy
Logistic Regression	76%	76%
Linear SVM	76%	76%
Decision Tree	83%	83%
Random Forest	87%	85%
Gradient Boost Tree	96%	82%

Logistic Regression and Linear SVM both did not perform well on both training and test set. Decision tree performed considerably well on both training and test set.

Random forest also performed well on both training and test set and gave the highest test accuracy. Gradient boost tree performed extremely well on training data but did not do well on test data as much. This clearly indicates that the Gradient Boost tree is overfitting the training data. This is because Gradient Boost Tree is having a high variance problem. Hence the optimum model considering the bias variance trade-off is the Random forest model with 200 trees.

VII. CONCLUSION

Hence an optimum model is found using bias variance trade-off analysis and the income of new entries is predicted with 85%confidence.

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